ESSAYS ON SCHOOL SIZE AND STUDENT PERFORMANCE, HAY YIELD AND WEATHER VARIATION, AND ECONOMIC DEVELOPMENT PROGRAM EVALUATION

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ESSAYS ON SCHOOL SIZE AND STUDENT PERFORMANCE, HAY YIELD AND WEATHER VARIATION, AND ECONOMIC DEVELOPMENT PROGRAM EVALUATION

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Abstract: Spatial econometrics deal with spatial interaction effects. Models incorporating neighboring effects are more appropriate in education economics, production economics, and regional science. In this dissertation, spatial econometric techniques are applied to account for spatial dependence of student performance, spatial heterogeneity of hay yields, and spatial spillover effects of economic development investments.

The first essay examines the possible endogeneity of school size and spatial dependence of student academic performance using a two-stage spatial quantile regression approach. Data from 424 Oklahoma high schools for the 2014-2015 school year is analyzed to investigate the relationship between school size and student academic achievement. After controlling for potential endogeneity of school size, the results indicate that school size is negatively related to average GPA and ACT score, with larger impacts for the lower and upper percentiles of average GPA and the lower and median percentiles of average ACT score. Significant spatial effects are found only for average GPA, suggesting that the average GPA is influenced by neighboring schools.

The second essay quantifies possible heterogeneous impacts in hay yield responses to weather variations in Oklahoma. Using panel data on hay yield for Oklahoma's 77 counties from 1977 to 2007, four distinct econometric models are specified. Each model allows for a different method of estimating the local effects of weather variation on hay yield. Results suggest that there are geographic variations of hay yield in response to weather variations.

The third essay reexamines whether or not the effect of the Economic Development Administration's (EDA) Public Works Program remains consistent with what was previously described in the literature. Using data on county-level employment from 2010 to 2014, the previous analysis is extended by incorporating a spatial econometric approach to examine the existence of potential spillover effects into neighboring counties. The results indicate that EDA investments not only have a significant positive effect upon the targeted counties' employment, consistent with what was found in the original study but also have significant positive effects upon neighboring counties' employment levels.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

SCHOOL SIZE AND STUDENT PERFORMANCE: A TWO-STAGE SPATIAL QUANTILE REGRESSION APPROACH TO EVALUATE OKLAHOMA HIGH SCHOOLS

Abstract

Debate about the impacts of the size of public schools upon academic performance has been ongoing in the U.S. since the 1960s, and studies offer conflicting results. This study adds to the body of evidence using a two-stage spatial quantile regression model, to account for possible endogeneity of school size and spatial dependence. Data from 424 Oklahoma high schools for the 2014-2015 school year was analyzed, considering school-level grade point average and average ACT score as the dependent variables. After controlling for potential endogeneity, the results suggest that school size is negatively related to both measures of student performance, with larger impacts for the lower and upper quantiles of average GPA and the lower and median quantiles of average ACT score. In particular, the impact of being in a larger school changes from positive to negative for average ACT score. Significant spatial effects were found only for average GPA, suggesting that the average GPA is influenced by neighboring schools. Smaller high schools, including those in rural areas, may have an advantage in terms of student performance by engaging parents and enhancing the efficiency of educational processes.

Introduction

School performance in the United States is a hotly debated issue. Public schools in the U.S. have been perceived to be in a declining phase of performance since the 1960s (Marlow, 2000). In 2013, U.S. Secretary of Education Arne Duncan warned that the "educational challenge in America is not just about poor kids in poor neighborhoods, it's about many kids in many neighborhoods". He made this statement after the results of the Program on International Student Assessment (PISA) were announced, which showed the U.S. school education system in poor light in international comparison. In addition, there are wide gaps in educational quality within the U.S. (Hanushek, Peterson, and Woessmann, 2014). Due to the significant practical implications of this perceived decline, considerable research effort has been applied to analyze this issue. One major strand of this literature is determining the impacts of schooling inputs – for instance, the characteristics of students, families, teachers, and schools – on student scholastic performance measures (Rivkin et al., 2005).

The size of individual schools and/or classes is a critical input measure of an educational institution. Larger schools were seen as having distinct advantages over smaller ones mainly from economies of scale, as lower administrative costs were highlighted as beneficial (Cohn, 1968; Kenny, 1982). For example, studies on the relationship between school size and student performance found a positive relationship between larger schools and student achievement (Barnett et al., 2002; Bradley and Taylor, 1998; Schreiber 2002). Other factors favoring larger schools are their ability to engage students from diverse backgrounds, less "pigeonhole" effect in successive student cohorts, and greater flexibility in offering specialized courses (Leithwood and Jantzi, 2009). Recently, justifications supporting larger schools have been challenged by empirical evidence (Leithwood and Jantzi, 2009; Stevenson, 2009). In particular, smaller schools demonstrated better academic results – suggesting that bigger is not always better (Stevenson, 2009; Humlum and Smith, 2015). As noted by Kuziemko (2006), smaller schools perform better academically due to closer ties between teachers, students, and parents. Smaller schools also make students feel safer, and students are less likely to get "lost in the crowd" (Harris, 2006, p.137).

However, the debate on the impact of school size on student academic performance is not yet fully resolved. According to Kuziemko (2006) even though there is no consensus among existing studies on the impact of school size on student performance, more studies have found a negative impact than a positive impact. In comparison to magnitude and depth of economic studies on the impact of *class size* on student performance, corresponding economics literature on the impact of *school size* is relatively meager (Kuziemko, 2006; Humlum and Smith, 2015). Moreover, some previous studies have suffered from econometric modeling issues such as the omission of relevant explanatory/control variables like costs (Harris, 2006). Since the cost element associated with school size is of particular importance to administrators and policymakers, such misspecification could lead to misleading conclusions. For example, Hoagland (1995) found that when expenditures are controlled for, overall school size did not predict student performance. Recently, studies have addressed the issue of potential endogeneity of class size with respect to student achievement with an instrumental variables approach using two-stage least squares. For instance, Hoxby (2000) estimated the effects of class size on student achievement using natural variation in the school-aged population generated by parents' choices and found that reductions in class size have no effect on student performance. Levin (2001) found class size reduction incorporated with peer effect may play an important role in enhancing scholastic achievement.

Little research has been done to explore the impact of school size on student performance, specifically using Oklahoma high school data. Using data from the mid-1990s, Jacques, Brorsen, and Richter (2000) found that creating larger schools through consolidation resulted in decreased test scores. Whitacre and Taylor (2016) found that the impact of school size on student performance varies in terms of how a high school is defined as being “small”.

In this study, we propose to estimate the impact of school size on student scholastic performance by analyzing a cross-section of Oklahoma high-schools. Our study is an attempt to empirically answer one of the important questions in economics of education: does school size really matter in determining student academic achievement? Two distinct measures, the average Grade Point Average (GPA) for the senior class and the average ACT score, are used as measures of student performance. We check the robustness of our findings by using different regression specifications: conditional mean models without (the ordinary least-squares, OLS, estimator) and with spatial dependence in student performance; and conditional quantile functions without and with spatial dependence in student performance. We also use instrumental variables to account for the possible endogeneity of school size with respect to student scholastic achievement. We use a measure of parental motivation as an instrument for school size. These conditional mean and quantile estimates can be used to make different interpretations of the impacts of a change in school size on student performance (Levin, 2001). The estimated conditional mean measures the average causal effect, i.e., the effect of a change in school size on the academic performance of the average individual in the sample. This estimate shows the impact of a change in school size in changing the performance of the average student. In contrast, the quantile estimates show the marginal effects of a change in school size on the performance of students at different points in the conditional distribution of student performance. Moreover, the quantile estimates show the equity (distributive) implications of a change in school size. In essence, quantile estimates help better understand how much effect would be experienced by whom; for example, quantile estimates illustrate the impact on marginal achievers and students at risk of failing, and not just the average performer. This type of specification may be particularly relevant given the skewed distribution of public high school achievement (and size) across Oklahoma.

The assumption of spatial dependence is of particular relevance in our context. This stems from previous studies that have found spatial dependence exerted through school size in educational achievement measures. For example, Angrist and Lavy (1999) found that larger schools (in terms of enrollment) tend to be located in larger cities catering to prosperous families, while schools with smaller enrollments tend to be located in rural areas catering to comparatively poorer households. Due to this, the difference in socioeconomic status of students within a school tends to be less; this will also affect the class sizes assigned to schools. Therefore, enrollment and neighborhood socioeconomic status have a positive association (Murnane and Willett, 2011). Studies on neighborhood effects on educational outcomes suggest that the affluent neighborhood's educational climate is likely to have a positive association with school performance, such as high school graduation rate and grades/test scores (Crowder and South, 2011; Nieuwenhuis and Hooimeijer, 2016). When parents can choose school districts to send their children, schools tend to get pressure to improve to attract and retain students, and hence lead to better school performance. Spatial dependence might occur when schools compare their performance with their neighboring schools'. In this context, average GPAs tend to be correlated with those of neighboring schools, while average ACT scores do not tend to be spatially dependent. Therefore, in order to account for the spatial interdependent effect of neighboring schools on school academic performance measures, a spatial econometric modeling approach is more appropriate. Brasington (2007) analyzed competition between public and private schools in Ohio and estimated the relationship between outcomes from a private school and the number of public-school districts in the county. The results were sensitive to model specification; i.e., a model without spatial dependence showed competitive effects, but a model with spatial dependence mostly did not show competitive effects. As proposed by Brasington (2007), we make use of spatial dimension of the data to address spatial spillover effects of public schools on school performance and to minimize the omitted spatial variables bias.

Econometric procedure

The most basic model in this study estimates the influence of school size on student achievement as follows:

(1) $$y_i = \alpha + \beta x_i + \delta z_i + \varepsilon_i,$$

where y_i is the outcome variable of interest (average senior GPA or average ACT score) at school i, x_i is a vector of control variables, for instance, characteristics of students, families, teachers, and schools, z_i is the school size measured as logarithm of total enrollment in the school, α, β, and δ are the parameters to be estimated, and ε_i is the random error term. Model (1) is initially estimated using the OLS estimator. It has been shown previously that the class size variable could be determined endogenously along with student performance (Hoxby, 2000; Levin, 2001). In particular, Hoxby (2002) described that the potential endogeneity of the class size can be occurred by unobserved parents' responses to their children's school size being unusually large, such as the parents might decide to move to another school district or might choose to send their children to a private school. For instance, in equation (1), the estimate of δ is unbiased if z_i is not correlated with ε_i (i.e.,$cov(z_i, \varepsilon_i) = 0$). However, if z_i is correlated with ε_i (i.e., $cov(z_i, \varepsilon_i) \neq 0$), then the estimate of δ will be biased.

Suppose the school size is correlated with parents' motivation, which is not observed. In that case, the estimated effect of school size on student performance will be biased from omitting relevant schooling inputs associated with school size. For example, highly motivated parents might choose a smaller school size given the fact that the number of teachers per enrolled student is higher. These highly motivated parents might also devote more time to their children's education. Walsh (2010) showed that parental involvement decreases as the size of schools increases, though the magnitude of effect is relatively small. Previous studies examined the impact of parental involvement on children's education found a positive relationship between parental involvement and their children's academic achievement (Stevenson and Baker, 1987; Izzo et al., 1999; Fan and Chen, 2001; Jeynes, 2007; Tan and Goldberg, 2009). To reduce this endogeneity bias from omitted variables in estimates of the effect of school size on student achievement, we use instrumental variables that measure the motivation of the parents. This variable is measured as both the percentage of parents attending parent-teacher meetings and the average number of days absent. Using these instruments, the model is estimated using a two-stage least squares (2SLS) estimator as follows:

$$y_i = \alpha + \beta x_i + \delta \hat{z}_i + \varepsilon_i, \tag{2}$$

$$z_i = \gamma_0 + \gamma_1 x_i + \gamma_2 m_i + v_i, \tag{3}$$

where m_i is a vector of instrumental variables. In the first stage, equation (3) is estimated using OLS and then the fitted values of z_i are used in the second stage where equation (2) is estimated. This specification controls for the possible endogeneity of z_i and thus allows for asymptotically unbiased estimate of the parameter of interest (δ).

The next model estimated is the basic quantile regression model, which is the quantile analog of equation (1), using the least absolute deviation (LAD) estimator. That is, the influence of x_i and z_i on y_i is estimated at different points of the conditional distribution of y_i. The estimation is carried out as proposed in Koenker and Bassett (1978) by minimizing the objective function given in equation (4) as follows:

$$\underset{\beta,\delta \in R^K}{\text{Min}} \left[\sum_{i \in \{i: y_i \geq \beta x_i + \delta z_i\}} \tau |y_i - \beta x_i + \delta z_i| + \sum_{i \in \{i: y_i < \beta x_i + \delta z_i\}} (1-\tau)|y_i - \beta x_i + \delta z_i| \right], \quad \tau \in (0,1), \tag{4}$$

where K is the dimension of vector of explanatory variables, and τ is the quantile of the distribution of y_i.[1] We next estimate the models (2) and (3) using the two-stage LAD (2SLAD) estimator developed by Ameiya (1982).[2] The 2SLAD works similar to 2SLS; in the first-stage, the OLS estimator is used to estimate model (3); and in the second stage, model (2) is estimated using the LAD estimator for given quantiles (τ).[3] The benefit of the quantile regression model over simple OLS is that, in many cases, the relationship in question may be non-linear (and thus violate the assumption of OLS). Alternatively, the relationship may be adequately explained by latent moderators such as quantiles of the distribution of the dependent variable. In our case, a scatter plot of student performance against school size would describe a distribution that is asymmetric or non-identical over the levels of school size. Thus, quantile regression would reveal differences in the influence of school size on student performance at different quantiles of conditional distribution of student performance.

None of the previous models account for possible spatial dependence in the factors influencing student achievement. To preliminarily test whether special autocorrelation exists, the Moran's *I* test can be conducted on the residuals of OLS and 2SLS models for student academic performance. In the next set of models, we use the spatial dimensions of the data by weighting the observations with spatial weights. First, a neighborhood contiguity object is created using the school latitude and longitude information. Next, this contiguity object is used to create a spatial weight matrix.[4] While there are a host of possible spatial models to explore[5], we begin with a

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[1] Eide and Showalter (1998) use the LAD estimator to analyze the impact of school quality variables on student achievement.
[2] Levin (2001) uses this estimator to study the effect of class size on student achievement.
[3] Standard errors are obtained by bootstrapping equation (2). The "quantreg" package of Koenker (2016) using the R programming language (R Core Team, 2017) is used for the analysis.
[4] We followed the description in Bivand, Pebesma, and Gomez-Rubio (2013) for creating spatial weights. We used the packages "ggmap" (Kahle and Wickham, 2013), "sp" (Pebesma and Bivand, 2005), "spdep" (Bivand and Piras, 2015; Bivand, Hauke, and Kossowski, 2013), and "pgirmess" (Giraudoux, 2017) available in the R programming language. We first identified 5 nearest neighbors of spatial units using Euclidean distance. These 5 nearest neighbors list was converted into spatial weights object with row-standardized style.
[5] Elhorst (2010) reviews spatial econometric models.

simple spatial lag model to capture the possible influence of nearby schools. The spatial lag model (SAR) estimated is as given:

$$Y = \rho WY + \alpha + X\beta + \varepsilon, \tag{5}$$

where Y denotes a vector of the outcome variable of interest (average GPA or average ACT score), W is the spatial weight matrix – and so WY captures the impacts of neighboring school outcomes, X denotes a vector of independent variables, ρ represents the spatial autoregressive coefficient, α and β are the parameters to be estimated, and ε is a vector of disturbance term. The model is estimated using the maximum likelihood estimator. A step beyond the SAR model is the spatial Durbin model, which is with the following form:

$$Y = \rho WY + \alpha + X\beta + WX\theta + \varepsilon, \tag{6}$$

where WX denotes the endogenous interaction effects among the independent variables and θ represents a fixed parameter to be estimated. The model contains spatially lagged independent variables along with the lagged dependent variable on the right-hand side. The benefit of this model is that it introduces spillover effects from neighboring region's independent variables, such as school expenditures. We also test a spatial error model:

$$Y = \alpha + X\beta + u, \tag{7}$$

$$u = \lambda Wu + \varepsilon, \tag{8}$$

where Wu denotes the interaction effects among the disturbance terms of the different spatial units and λ represents the spatial autocorrelation coefficient.

After testing each of these spatial models and assessing their results by implementing the classic LM-tests and the robust LM-tests[6], our final model is the quantile version of the spatial

[6] Both the tests are implemented based on the residuals of the OLS model and follow a Chi-squared

autoregressive model (5) developed by Kim and Muller (2004). The estimated conditional quantile model is as given:

$$Y = \rho_{(\tau)} WY + X\theta_{(\tau)} + u \quad (9)$$

where τ is the τ^{th} quantile of the conditional distribution of average GPA for senior class or average ACT score. Due to the presence of the lagged dependent variable in (9), the conventional quantile estimates would be inconsistent. Kim and Muller's (2004) two-stage quantile regression (2SQR) and Chernozhukov and Hansen's (2006) instrumental variable quantile regression (IVQR) are two possible econometric techniques applicable in this situation. Both methods account for the general endogeneity problem in the quantile regression, and not the spatial lagged dependent variable specifically. However, both methods can be used to solve the endogeneity problem in the quantile regression (McMillen, 2013a). The IVQR method is applicable to smaller datasets and is computationally intensive (Kostov, 2009; Zhang and Leonard, 2014). Therefore, we used the 2SQR technique, available in the "McSpatial" package (McMillen, 2013b) in the R software (R Core Team, 2017). In the first stage, an instrumental variable is constructed for the lagged dependent variable (WY) using the predicted values from a quantile regression of WY on a set of instruments. In the second stage, the predicted values of WY are used in the quantile regression of Y on X. Standard errors are obtained from bootstrap with replacement as standard deviations of the bootstrapped coefficients.

Data

The data used in this study come from the Oklahoma Education Indicators Program (OEIP) funded by the Oklahoma Office of Educational Quality and Accountability. Profile reports at the district and school levels were obtained for the 2014-2015 school year.[7] There were 517 school

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distribution with one degree of freedom (Anselin, 1988; Anselin et al., 1996).

[7] The reports and the data for the years 1997-2016 are available at www.schoolreportcard.org.

districts in Oklahoma during the school year 2014-2015. After removing high schools with missing or incomplete information, data from 424 high schools are used for this analysis. The reports include information on community characteristics, educational processes, and student performance, such as the district poverty rate, school district administrative expenditures, and the average senior GPA and the average ACT score. Variable description and summary statistics are presented in Table 1. The average GPA across the 424 high schools is 3.11 and the average ACT score is 19.83. School size varies widely, with an average of 391 but with a high standard deviation.

To represent student performance, we focus on the average GPA for the senior class and the average ACT score. In the 2014-2015 school year, not all Oklahoma school districts offered students the ACT test, some offered the SAT. For those districts that offered the ACT test, for some districts, not all students in the district were required to take the ACT even when offered. The number of ACT tests administered at each school is available, but the percentage of students taking the ACT, out of the total students eligible to take the ACT at that school, is not available. Other tests used to measure academic performance in 2015 were End of Instruction (EOI) tests. These state mandated tests measured only whether students were "proficient" in a particular subject, and were administered to students at any grade level upon completion of that particular subject. Additionally, not all students were required to take an EOI assessment. A student could be determined to be "proficient" if they achieved a minimum score on a suitable alternative assessment including the ACT.[8]

Schooling inputs, including the characteristics of students, families, teachers, and schools are used as covariates across the specifications. School size is measured as natural logarithm of

[8] Oklahoma Statutes (70 O.S. § 1210.523 and 70 O.S. § 1210.525) and Oklahoma Administrative Code (OAC 210:10-13-16) provide procedures whereby alternate tests may be used by Oklahoma students to meet the ACE graduation testing requirements set forth in 70 O.S. § 1210.523. Documentation requirements are also set forth in OAC 210:10-13-16.
Available at https://sde.ok.gov/sites/ok.gov.sde/files/documents/files/ACE_16_Resources_Alt_List_051215.pdf

the total number of students enrolled in each high school. Student mobility[9] is measured as the percentage of new students enrolled in a school. The percentage of parents with some college education are used to represent family influence. Average years of teacher experience are used to measure as teacher quality.[10] The poverty rate at the district level is used for school district influence. Other variables, such as racial and ethnic composition of the school and/or school district, median household income, and the percentage of students receiving free lunch, were not included because a stepwise regression method did not select these other variables as important for determining student performance.

In addition to these schooling inputs, school district expenditures are used to control for potential omitted variables in estimating the effects of school size on student academic performance. District expenditures data were divided into eight categories; (i) instructional expenditures, (ii) student support services, (iii) instructional staff support services, (iv) district administration, (v) school administration, (vi) district support services, (vii) debt service, and (viii) other services. The expenditures per category are measured as logarithm of the actual dollars spent per average daily membership (ADM). The expenditures on both instructional and student support services are used as instrumental variables for school size in order to control for the potential endogeneity of school size with respect to student performance. Jacques and Brorsen (2002) examined the impact of school district expenditures on student performance using Oklahoma public school data and found that test scores are positively related to instructional expenditures, but are negatively related to student support services. Given this finding, we use only these 2 categories of expenditures (as opposed to all 8 listed above). The percentage of parents attending parent-teacher conference and the average number of days students were absent were used as instrumental variables, along with these two school district expenditures. In a two-

[9] Fowler-fin Fowler-Finn (2001) and Parke and Kanyongo (2012) found that student mobility is negatively associated with academic performance.
[10] Greenwald, Hedges, and Laine (1996) described the quality of teachers, including teacher experience is strongly related with student achievement in their meta-analysis.

stage regression model, we first estimate the school size with instrumental variables. We then estimate the student performance using the predicted values of school size.

Results

The preliminary results from the estimated relationships between school size and the two common measures of student performance, the average GPA and ACT scores, are illustrated in Figures 1a and 1b, respectively. There is a negative relationship between average GPA and school size with a decreasing effect as school size increases, indicating that smaller schools perform better than larger ones in terms of average GPA (Figure 1a). In contrast, average ACT shows a slightly negative relationship among smaller schools, but becomes positive as school size increases with a substantially increasing effect suggesting that larger schools outperform smaller ones for this measure (Figure 1b). These highly statistically significant non-linear relationships between school size and student performance suggest that a quantile regression approach is more appropriate for determining the effect of school size on each measure of student performance without specifying any non-linear functional forms for the model.

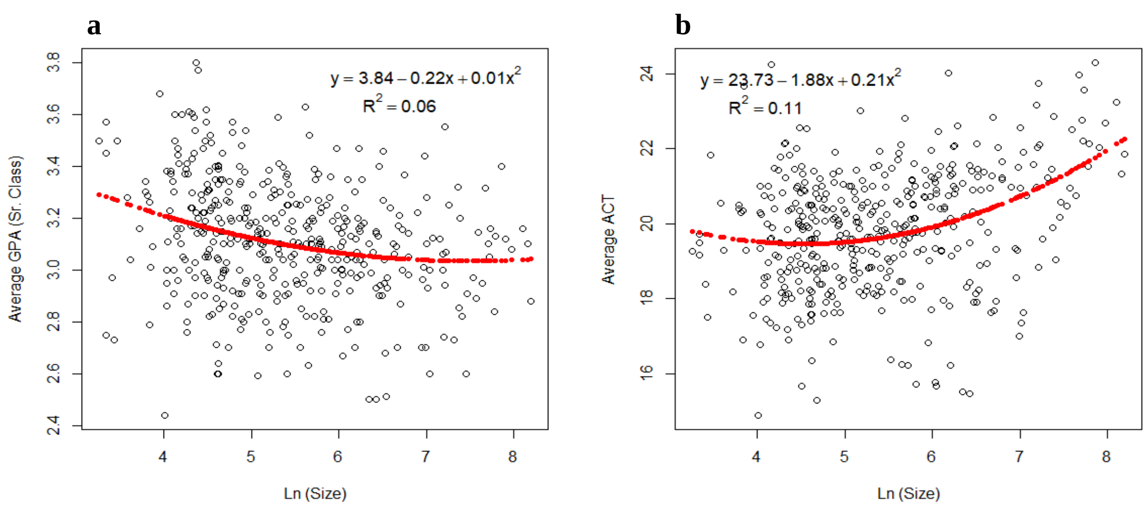


Figure 1-1 School size effect on average GPA and ACT scores in Oklahoma high schools

OLS and Quantile Regression Results

The estimation results from OLS and the five common quantile (i.e., the 10th, 25th, 50th, 75th, and 90th percentiles) regressions considering the school size variable as exogenous are presented in Table 2. The corresponding quantile regression plots are illustrated in Figures 2 and 3 for average GPA and ACT scores, respectively. The OLS results show a significant effect of school size on both the average GPA and the average ACT score, but in opposite directions. This implies that smaller schools are beneficial to the average GPA but that larger schools perform better on the average ACT score. These results are quite consistent with what the plots in Figures 1a and 1b have suggested based on treating school size as exogenous and without imposing any non-linear functional forms. As expected, other variables such as the percentage of parents with some college education, the poverty rate at the school district level, the average years of teacher experience, and the percentage of new students enrolled, are significantly different from zero for each measure of academic performance. An increase in the proportion of parents with some college education is consistent with increased average GPA and ACT scores, indicating that the parents' educational level plays a significant role in students' academic performance. School districts with higher poverty rates and schools with greater student mobility have lower academic achievement in both the average GPA and ACT scores. Interestingly, an increase in the average years of teacher experience has little effect on the average GPA, but has a greater positive effect on the average ACT score, indicating that teacher experience is a crucial factor in increased average ACT score.

For the quantile regression estimates, a significant effect of school size was found for both the average GPA and ACT scores. Students at the 25th and higher percentiles (not at the 10th percentile) of the conditional distribution of average GPA significantly benefit from a decrease in school size. On the other hand, students at all percentiles of the conditional distribution of average ACT substantially benefit from an increase in school size. The parents' educational level has a significant positive effect across all quantiles of each measure of student academic performance. The effect size of the parents' education level decreases as it moves from the 25th to the 75th quantiles for each measure of student performance. The school district poverty rate disadvantaged students below the 50th percentile of the conditional distribution of average GPA and students of all percentiles of the conditional distribution of average ACT score. The magnitude of the effect of the district poverty rate on average ACT score generally decreases as it moves to the higher quantiles. Interestingly, teacher experience has almost no significant impact on average GPA, however it has a significant positive effect on average ACT score across all quantiles. Student mobility has a significant negative effect across all but the 90th percentile on both the average GPA and ACT scores, and it has an insignificant effect on the 50th percentile of average ACT score. The effect size of student mobility considerably decreases as it moves from the 10th to the 75th percentile. Generally, these results reinforce that important differences do exist across the distributions of GPA and ACT scores, including the school size parameters which vary from the aggregate OLS values.

Before considering the estimates of the two-stage regression model, we first attempt to test and control for the potential endogeneity of school size with respect to student performance. If school size is endogenous, the OLS and quantile estimates are biased by correlation between school size and unobserved factors that vary with school size (i.e., factors that are difficult to quantify such as parental motivation and the efficient use of school resources). Parents with high motivation for student achievement may choose school districts with smaller school sizes. On the other hand, the school districts with larger school sizes may offer economies of size that are beneficial for students' academic performance. Table 3 presents the estimation results for the Hausman test for the school size being exogenous. School size is estimated from the reduced form equation (3) using four instrument variables: the percentage of parents attending parent-teacher conferences, the average days absent, and instructional expenditures and student support services per student enrolled, along with other explanatory variables. The first-stage estimates of the school size model are presented in Table 7 in Appendix. The results indicate that the instrument variables used are strongly correlated with school size. We then take the residuals of the reduced form equation and include them into the structural equation (2) in order to test the statistical significance of the coefficient upon the residuals in the structural equation. The *p*-values for the estimates of the residuals for both the average GPA and ACT scores are less than 0.01, respectively, so we can reject the null hypothesis that these residuals are irrelevant. In other words, there is evidence that school size is endogenous with respect to both the average GPA and ACT scores. This is consistent with other studies examining the potential endogeneity of school/class size along with student academic achievement (Hoxby, 2000; Levin, 2001).

Next, we examined the validity of instrument variables to identify the model and conduct the estimation of the school size effect within the structural equations framework. The instrument variables need to be correlated to the endogenous variable of school size, uncorrelated to the error term, and should not be a part of the model that explains the dependent variable, average GPA or average ACT score, used to measure student performance. We used the first stage regression model to test whether the instruments chosen are strongly correlated to the endogenous variable of school size. The value of Wald's *F* statistic is 18.841 with a *p*-value less than 0.01. The degree of freedom is 3 (the number of instruments minus the number of endogenous variables) and the critical value at 5% level for the χ^2 distribution with 3 degrees of freedom is 7.82. Hence, we can clearly reject the null hypothesis that the instruments are irrelevant. Additionally, we implemented the Sargan test for instrument validity.[11] We take the residuals from the second stage regression models for both the average GPA and ACT scores and use them as the dependent variables in both new regressions in which the residuals are estimated on all exogenous explanatory variables and all instruments. If the instruments selected are valid, they should be

[11] Stanca (2006) implemented the Sargan test for instrument validity of the effects of unobserved factors correlated with attendance to estimate the impact of attendance on academic performance.

uncorrelated to these residuals. We apply the χ^2 test with 3 degrees of freedom and calculate the sample size $n * R^2$ for the test statistic. The *p*-values of this test are 0.103 and 0.2 for the average GPA and ACT scores, respectively, and hence we do not reject the null hypothesis of the validity of instruments.

Two-stage Least Squares and Quantile Regression Results

We now turn to the structural estimation of the model. The estimation results from the 2SLS and 2SLAD models for the five common quantile regressions are presented in Table 4. The corresponding 2SLAD quantile regression plots for the average GPA and ACT scores are illustrated in Figures 4 and 5, respectively. The most striking finding from the two-stage model specification is the effect of school size on the average ACT score. The school size now has a significant negative effect on this measure of student performance, contrary to the positive effect observed in the OLS estimate. This suggests that once endogeneity is controlled for, smaller schools have an advantage, perhaps due to parental motivation or the efficient use of school district administrative expenditures. The school size effect on the average GPA remains the same as the OLS estimate, although the magnitude of the coefficients increased. The mean effects of the percentage of parents with some college education, the average years of teacher experience, and the percentage of new students enrolled all remain significant and retain their original signs for both the average GPA and ACT scores. The school district poverty rate has no significant mean effect on either measure of student performance unlike the OLS estimate. It is important to point out that controlling for the endogeneity of school size through parental motivation and school district administrative cost efficiencies could suppress the influence of disadvantageous school district poverty rates on each measure of student performance.

Shifting to the 2SLAD estimates, the effects of school size predetermined by both parental motivation and the efficient use of school district educational funds are roughly similar for the average GPA and ACT scores: both are significant and negative, indicating that smaller schools outperform larger ones for each measure of student performance. While smaller schools are beneficial for the average GPA to all students, they are only beneficial for the average ACT score for students at the 10^{th} and 50^{th} percentiles. The effect of the percentage of parents with some college education is quite important for each measure of student performance, it is significantly positive across all quantiles with a strikingly larger magnitude than any of the other variables considered. Interestingly, an increase in the school district poverty rate is only disadvantageous to students in the upper quantiles of the average ACT score. Given the negative effect of school size predetermined by parental motivation and school district educational expenditures, it is possible that the influence of predetermined school size may suppress the influence of disadvantageous school district poverty rate to students across all quantiles of GPA and ACT scores with the exception of students in the upper quantiles of ACT score. Teacher experience has no significant impact on the lower quantiles and a significant but small effect upon the upper quantiles of the average GPA. For the average ACT score, teacher experience has a significantly positive effect across all the quantiles although the magnitude of this effect decreases in the higher quantiles. Student mobility has a significant negative impact across all quantiles except the 90^{th} percentile on the average GPA and only a significant negative effect on the 25^{th} and 75^{th} percentiles for the average ACT score.

To sum up the results from the OLS and the two-stage regression models, the estimated effects upon both student performance measures are consistent for the percentage of parents with some college education, teacher experience, and student mobility. The effect of school size on the average ACT score and the effect of school district poverty on the average GPA are inconsistent. The school size effect on the average ACT is significantly positive for the OLS regression, but is significantly negative for the two-stage regression. This is an important finding, suggesting that controlling for the potential endogeneity of school size can change the direction of the relationship between school size and school performance measure.

Finally, in order to incorporate possible spatial spillover effects of public school districts into our structural equations model and control for the potential omitted variable bias, we first test whether there are spatial effects on student academic performance from neighboring school districts. If spatial effects are not considered, the estimator of the coefficients for the remaining variables will be biased and inconsistent by omitted relevant explanatory variables (Greene, 2005). The Moran's *I* test results on the residuals of the OLS and 2SLS models for the average GPA and ACT scores, using the five-nearest-neighbors weight matrix, find that there is evidence of spatial correlation of the average GPA between nearby schools, but not for the average ACT score. The Moran's *I* plots on the residuals of two-stage models for average GPA and ACT scores are illustrated in Figures 6a and 6b, respectively. For the average GPA, the Moran's *I* statistics are 0.047 and 0.058 and their corresponding *p*-values are 0.045 and 0.018, respectively (Figure 6a). Based on the results we reject the hypothesis that the OLS and 2SLS residuals are independently distributed across space, indicating that there are some unobserved characteristics causing a school's GPA to be correlated among nearby schools' GPA. But for the average ACT

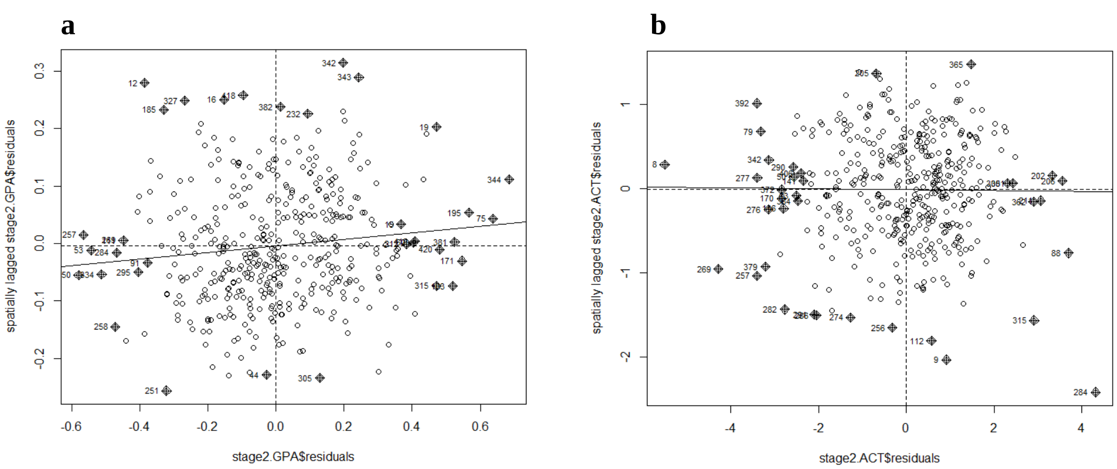


Figure 1-6 Moran's *I* plots on the residuals of two-stage models for GPA and ACT scores

score, the Moran's *I* statistics are -0.003 and -0.005 and their corresponding *p*-values are 0.508 and 0.534, respectively, indicating the hypothesis of no spatial correlation in the OLS and 2SLS residuals cannot be rejected (Figure 6b).

The Moran's *I* test results suggest that it is necessary to include spatial effects for the average GPA model. However, the Moran's *I* test alone is unable to demonstrate whether a spatial lag model or a spatial error model is more appropriate. Therefore, we need to estimate some spatial models to identify the exact source of spatial dependence. Table 5 presents the estimation results from each spatial econometrics model for the average GPA.[12] We found the spatial lag effect on the average GPA to be statistically significant at the 1% level, suggesting that a school's average GPA is positively associated with its neighboring schools' average GPA. In particular, the parameter estimate suggests that a 1-point increase in GPA by neighboring schools will raise a school's GPA by 0.175 points. The spatial error model indicates that there is insignificant spatial effect on unobserved factors in a school's average GPA from unobserved factors in its neighboring schools' average GPA. Interestingly, the spatial Durbin model found that the size of the neighboring schools has a significant effect at the 1% level on the average GPA. The average GPA of a school is negatively related to its neighboring schools' sizes. However, the estimated spatial lag effect of the Durbin model on the average GPA is no longer significant. Additionally, we estimated the spatial Durbin model and the spatial lag of X model both with only the spatially lagged school size. The results obtained were similar to the spatial Durbin model. In particular, the Moran's *I* test on the residuals of the spatial lag of X model indicates that there is some spatial correlation not fully specified.

We choose the spatial lag model to estimate the spatial quantile regressions because the estimated effects of other schooling inputs on the average GPA (including the spatial lag effect)

[12] After testing each of the spatial econometrics model specified for both the average GPA and ACT scores, we found no statistically significant spatial effects on the average ACT score from neighboring school districts. Therefore, the spatial models are only estimated for the average GPA.

are significant, the values of AIC for both models are essentially the same, and the value of BIC for the spatial lag model is smaller. Furthermore, the Moran's *I* test on the residuals of the spatial lag model with the five-nearest-neighbors weight matrix confirmed this result. In particular, after controlling for the omitted spatial lag effect, the Moran's *I* statistic is no longer positive and significant (i.e., the statistic is -0.768 and the *p*-value for the statistic is 0.779), suggesting that there is no spatial correlation in the residuals of the spatial lag model.

Two-stage Spatial and Quantile Regression Results

Finally, we turn to the estimates of the spatial lag and two-stage spatial lag for the five common quantile regressions. The results are presented in Table 6. In the spatial lag model, the spatial lag effect on a school's average GPA from its neighboring schools' average GPA is significantly different from zero in the inter-quantile range. For the two-stage spatial lag model, this effect is significant across all quantiles with the greatest magnitudes estimated at the 10^{th} and 90^{th} percentiles. Both models found a school's average GPA to be positively correlated to its neighboring schools' average GPA. The parameter estimates suggest that a 1-point increase in GPA by neighboring schools results in increases of 0.38 to 0.78 units at that school. The estimated effects of the percentage of parents with some college education, teacher experience, and student mobility, and their significance and sign, are consistent between the two models. However, the estimated effects of school size and the school district poverty rate somewhat differ across models. Generally, both models demonstrate that smaller schools are beneficial for GPA in schools at or above the 75^{th} percentile for GPA. The school district poverty effect is significant in the interquantile range for the spatial lag model, but is insignificant across all quantiles for the two-stage spatial model. Although both models control for omitted variable bias by estimating the spatial lag effect of neighboring school districts, the two-stage spatial lag model is more robust by controlling for the endogeneity of both school size and neighboring schools' average GPA using relevant instrument variables.

Conclusion

A long-standing debate in educational economy is whether school size really matters in determining student performance. Earlier studies have been concerned with this topic focused on the overall causal relationship between school size and student achievement, but did not account for the possible endogeneity of school size and spatial dependence of neighboring schools' student performance. This study focuses on understanding how the effect of school size on student performance varies across different segments of the conditional distribution of student academic performance as measured by average GPA and ACT scores, using different econometric model specifications.

The results of the quantile regression show that the direction of the impact of school size varies across measures of student performance. In fact, there appears to be a negative effect of school size on average GPA, but there is a positive effect on average ACT score, which suggests that smaller schools are beneficial to average GPA but that larger schools perform better on average ACT score. The results find that the parameter estimates of school size effect differ across the distributions of average GPA and ACT scores, which are different from the OLS estimates.

The findings from the quantile approach of 2SLAD indicate that controlling for the endogeneity of school size using instrumental variables can change the direction and magnitude of school size impact on school performance measures. In particular, the parameter estimate of school size effect on average ACT score is changed from positive to negative and the coefficients of school size effects on both average GPA and ACT scores are increased in magnitude. The results suggest that, once endogeneity of school size is controlled for, smaller schools have an advantage, perhaps due to parental motivation and school district administrative cost efficiencies.

The results from the spatial model specification test find no significant spatial effects on average ACT score from 5-nearest-neighboring schools, suggesting that average ACT score is not influenced by neighboring schools. Therefore, the spatial model is only useful for estimating the relationship between school size and average GPA. The findings of the two-stage spatial quantile regression suggest that there appears to be a strong positive spatial autocorrelation between 5-nearest-neighboring schools' average GPA. However, controlling for the spatial effect on average GPA yields decreased school size impact in magnitude. In particular, the parameter estimates indicate that a 1% increase in school size result in decreases in average GPA by 0.14 at the 90th percentile to 0.15 points at the 75th percentile.

Overall, this study finds that smaller schools may be advantageous for improving student academic performance by engaging parents and community and enhancing the efficiency of educational system. However, it becomes clear that results are impacted by controlling for possible endogeneity and spatial effects. Therefore, different econometric techniques are needed for different measures of student performance in order to more precisely examine the causal relationship between school size and the performance of high school students.

Table 1-1 Descriptive Statistics for Oklahoma High Schools

Variable	Mean	Std. Dev.
Dependent		
Average GPA in senior class	3.11	0.23
Average ACT score	19.83	1.62
Independent		
Total number of students enrolled	391.75	544.42
Percentage of parents with some college education	0.18	0.08
Percentage of poverty	0.17	0.06
Average years of teacher experience	13.45	3.32
Percentage of new students enrolled	0.08	0.07
Instrument		
Percentage of parents attending parent-teacher conferences	0.54	0.24
Average days absent	10.17	4.15
Instructional expenditures ($/ADM)	258.12	142.33
Student support services ($/ADM)	565.98	207.53

Notes: AMD is the school districts' average daily membership (average enrollment).

Table 1-2 OLS and Quantile Regression Effects of Students, Families, Teachers, and Schools Characteristics on GPA and ACT

Dependent Variable		Quantile Regression					Dependent Variable		Quantile Regression				
GPA	OLS	t = 0.10	t = 0.25	t = 0.50	t = 0.75	t = 0.90	ACT	OLS	t = 0.10	t = 0.25	t = 0.50	t = 0.75	t = 0.90
Constant	3.41***	3.11***	3.26***	3.35***	3.66***	3.96***	Constant	16.59***	15.37***	15.63***	16.13***	17.40***	18.27***
	(0.08)	(0.17)	(0.10)	(0.08)	(0.12)	(0.13)		(0.49)	(1.16)	(0.95)	(0.64)	(0.41)	(0.68)
LnEnrollment	-0.07***	-0.03	-0.06***	-0.06***	-0.10***	-0.11***	LnEnrollment	0.27***	0.39***	0.28**	0.33***	0.27***	0.24***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)		(0.07)	(0.14)	(0.13)	(0.09)	(0.06)	(0.09)
College Education	0.69***	0.74**	0.85***	0.72***	0.66***	0.69***	College Education	6.58***	5.30**	8.35***	7.17***	6.93***	6.84***
	(0.16)	(0.34)	(0.21)	(0.15)	(0.15)	(0.22)		(1.00)	(2.72)	(1.80)	(0.86)	(1.04)	(0.91)
Poverty	-0.43***	-0.86**	-0.43**	-0.34*	-0.28	-0.69*	Poverty	-4.09***	-5.71***	-4.76***	-4.00***	-3.09***	-3.29**
	(0.17)	(0.42)	(0.20)	(0.18)	(0.21)	(0.36)		(1.08)	(2.25)	(1.70)	(1.01)	(0.97)	(1.62)
Teacher Experience	0.01**	0.00	0.00	0.01**	0.01	0.00	Teacher Experience	0.12***	0.09*	0.13***	0.12***	0.10***	0.08***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)		(0.02)	(0.05)	(0.04)	(0.03)	(0.02)	(0.02)
Student Mobility	-0.71***	-1.06***	-1.01***	-0.74***	-0.65**	-0.53	Student Mobility	-3.57***	-7.93***	-5.83***	-1.63	-2.36***	-1.63
	(0.14)	(0.28)	(0.23)	(0.23)	(0.28)	(0.33)		(0.91)	(2.56)	(2.21)	(1.45)	(0.70)	(1.38)

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level. Standard errors are shown in parenthesis.

Table 1-3 Estimation Results of the Hausman Test for Endogeneity of School Size

Dependent Variable	GPA	ACT
Constant	3.775***	19.953***
	(0.122)	(0.769)
LnEnrollment	-0.168***	-0.623***
	(0.028)	(0.176)
College Education	1.323***	12.483***
	(0.229)	(1.441)
Poverty	-0.192	-1.861*
	(0.178)	(1.119)
Teacher Experience	0.007**	0.118***
	(0.003)	(0.019)
Student Mobility	-0.700***	-3.453***
	(0.140)	(0.882)
Estimated Residual from the 1st Stage	**0.113*****	**1.058*****
	(0.030)	**(0.191)**
R^2	0.229	0.372
N	424	424
F	20.67	41.17

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level. Standard errors are shown in parenthesis.

Table 1-4 2SLS and 2SLAD Quantile Regression Effects of Students, Families, Teachers, and Schools Characteristics on GPA and ACT

Dependent Variable		2SLAD Quantile Regression					Dependent Variable		2SLAD Quantile Regression				
GPA	2SLS	t = 0.10	t = 0.25	t = 0.50	t = 0.75	t = 0.90	ACT	2SLS	t = 0.10	t = 0.25	t = 0.50	t = 0.75	t = 0.90
Constant	3.77***	3.71***	3.48***	3.71***	4.21***	4.28***	Constant	19.95***	19.74***	18.20***	19.99***	19.41***	18.48***
	(0.12)	(0.21)	(0.14)	(0.17)	(0.21)	(0.23)		(0.80)	(1.95)	(1.56)	(0.89)	(1.18)	(1.36)
Pred LnEnrollment	-0.17***	-0.20***	-0.13***	-0.16***	-0.22***	-0.23***	Pred LnEnrollment	-0.62***	-0.97**	-0.46	-0.57***	-0.15	0.20
	(0.03)	(0.05)	(0.03)	(0.04)	(0.04)	(0.05)		(0.18)	(0.49)	(0.34)	(0.19)	(0.28)	(0.34)
College Education	1.32***	1.88***	1.35***	1.25***	1.51***	1.44***	College Education	12.48***	10.92***	13.52***	13.02***	9.18***	7.11***
	(0.23)	(0.37)	(0.33)	(0.34)	(0.29)	(0.40)		(1.50)	(4.45)	(2.52)	(1.54)	(1.98)	(2.44)
Poverty	-0.19	-0.24	-0.31	-0.15	-0.17	-0.29	Poverty	-1.86	0.71	-2.37	-3.15***	-2.56**	-3.05*
	(0.18)	(0.32)	(0.26)	(0.21)	(0.24)	(0.40)		(1.16)	(2.68)	(1.97)	(1.28)	(1.32)	(1.66)
Teacher Experience	0.01**	0.00	0.01	0.01*	0.01*	0.01*	Teacher Experience	0.12***	0.12***	0.13***	0.11***	0.09***	0.08***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)		(0.02)	(0.04)	(0.04)	(0.03)	(0.02)	(0.03)
Student Mobility	-0.70***	-0.66**	-0.81***	-0.75***	-0.90***	-0.42	Student Mobility	-3.45***	-3.34	-5.20***	-1.93	-2.33***	-1.21
	(0.14)	(0.28)	(0.17)	(0.23)	(0.21)	(0.32)		(0.92)	(2.50)	(1.99)	(1.35)	(0.66)	(1.63)

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level. Standard errors are shown in parenthesis.

Table 1-5 Estimates of Spatial Models for Students, Families, Teachers, and Schools Characteristics on Average GPA

Dependent Variable	Spatial Lag			Spatial Error			Spatial Durbin		
GPA	Estimate	Std. Error	P-value	Estimate	Std. Error	P-value	Estimate	Std. Error	P-value
Constant	2.838	0.231	0.000	3.394	0.076	0.000	3.206	0.318	0.000
lnEnrollment	-0.064	0.011	0.000	-0.066	0.011	0.000	-0.046	0.013	0.000
College Education	0.653	0.154	0.000	0.665	0.160	0.000	0.616	0.175	0.000
Poverty	-0.425	0.166	0.010	-0.444	0.171	0.009	-0.544	0.181	0.003
Teacher Experience	0.007	0.003	0.032	0.007	0.003	0.025	0.006	0.003	0.069
Student Mobility	-0.692	0.140	0.000	-0.704	0.142	0.000	-0.675	0.140	0.000
*W*lnEnrollment							-0.068	0.022	0.002
*W*College Education							0.416	0.314	0.185
*W*Poverty							0.265	0.313	0.399
*W*Teacher Experience							0.004	0.007	0.539
*W*Student Mobility							0.003	0.296	0.993
ρ	0.175	0.067	0.011				0.099	0.077	0.196
λ				0.130	0.076	0.107			
AIC	-124.489			-120.679			-124.658		
BIC	-92.091			-88.281			-72.011		

Table 1-6 Estimates of Spatial Lag and Two-Stage Spatial Quantile Regression on Average GPA

Dependent Variable	Spatial Lag Quantile						Two-Stage Spatial Quantile				
GPA	t = 0.10	t = 0.25	t = 0.50	t = 0.75	t = 0.90		t = 0.10	t = 0.25	t = 0.50	t = 0.75	t = 0.90
Constant	1.93**	1.38*	2.09***	2.32***	4.68***	Constant	1.61	1.79**	1.74***	1.96***	1.42*
LnEnrollment	-0.04*	-0.03	-0.04***	-0.08***	-0.13***	Predicted LnEnrollment	-0.16***	-0.09**	-0.06	-0.15***	-0.14***
College Education	0.81**	0.50**	0.64***	0.60***	0.82***	College Education	1.68***	1.03***	0.77**	1.22***	1.11***
Poverty	-0.65	-0.51***	-0.35*	-0.49**	-0.51	Poverty	-0.19	-0.27	-0.33	-0.34	-0.31
Teacher Experience	0.00	0.00	0.01*	0.01	0.01	Teacher Experience	0.00	0.00	0.01**	0.01	0.00
Student Mobility	-0.84***	-0.99***	-0.81***	-0.73***	-0.52	Student Mobility	-0.65**	-0.63***	-0.79***	-0.74***	-0.39
WY	0.40	0.58***	0.38**	0.41*	-0.24	Predicted WY	0.64*	0.51**	0.50***	0.61***	0.78***

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level.

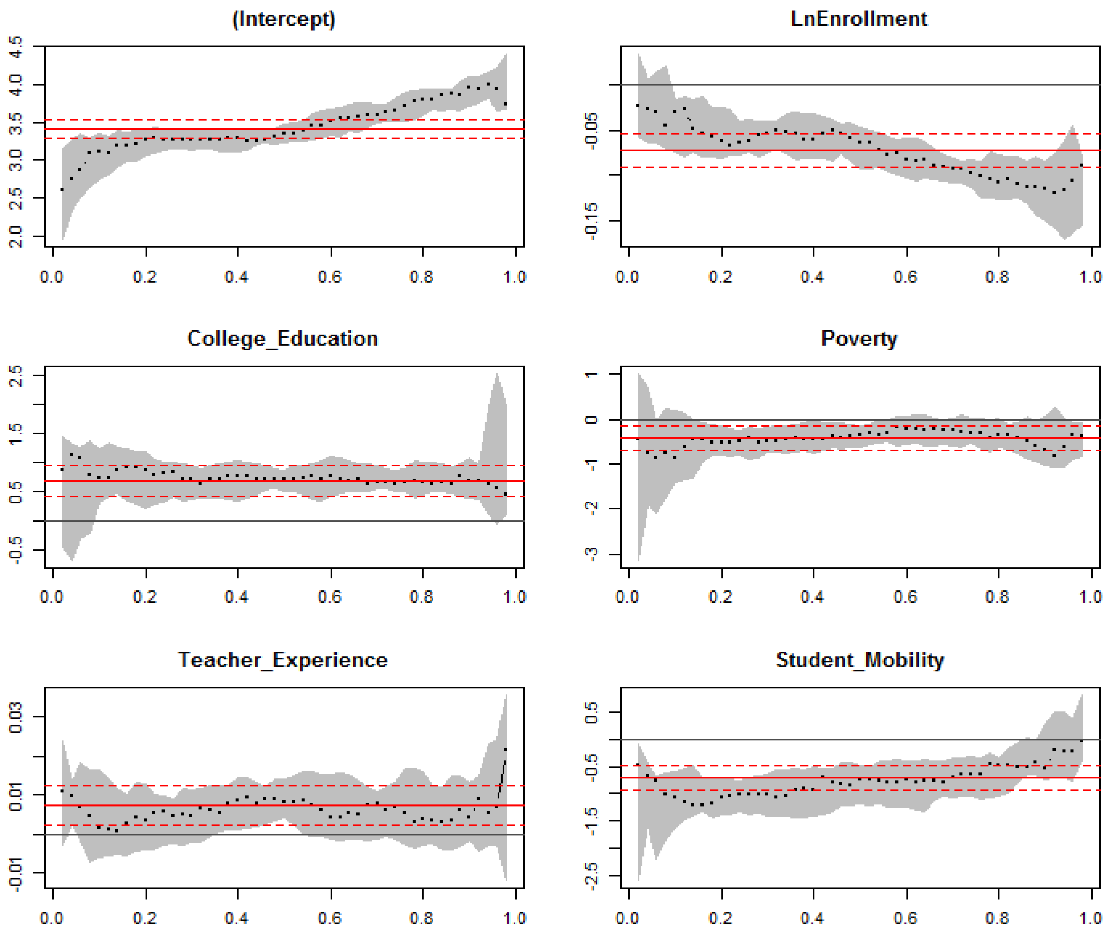


Figure 1-2 Quantile regression covariates effects for average GPA

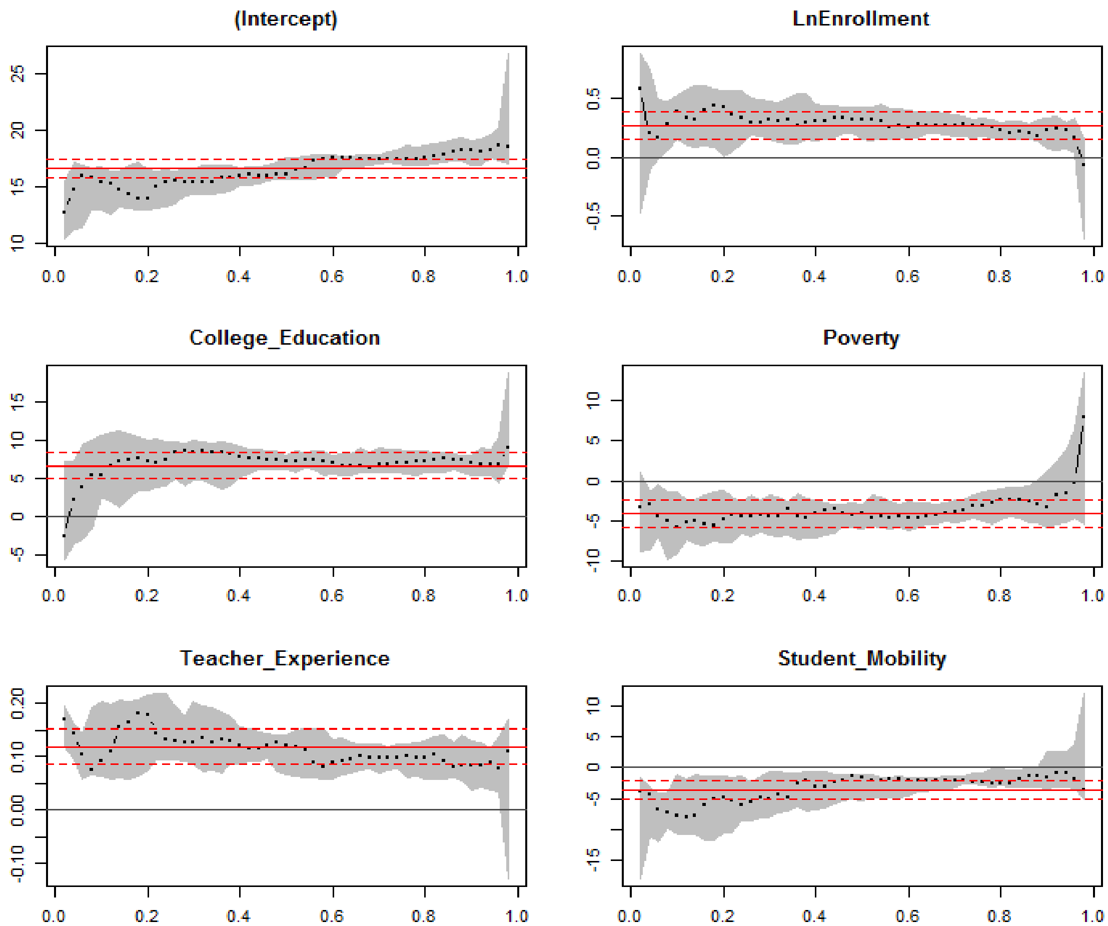


Figure 1-3 Quantile regression covariates effects for average ACT

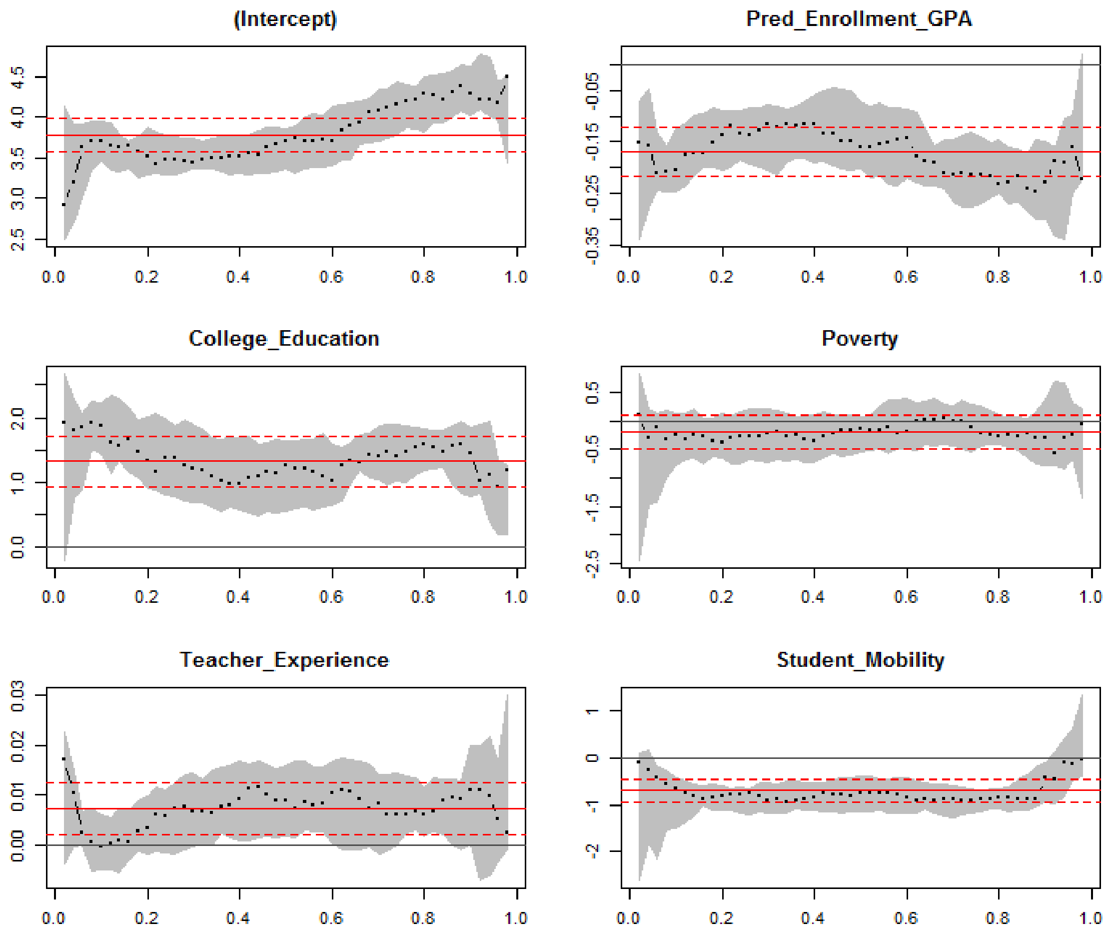


Figure 1-4 2SLAD quantile regression covariates effects for average GPA

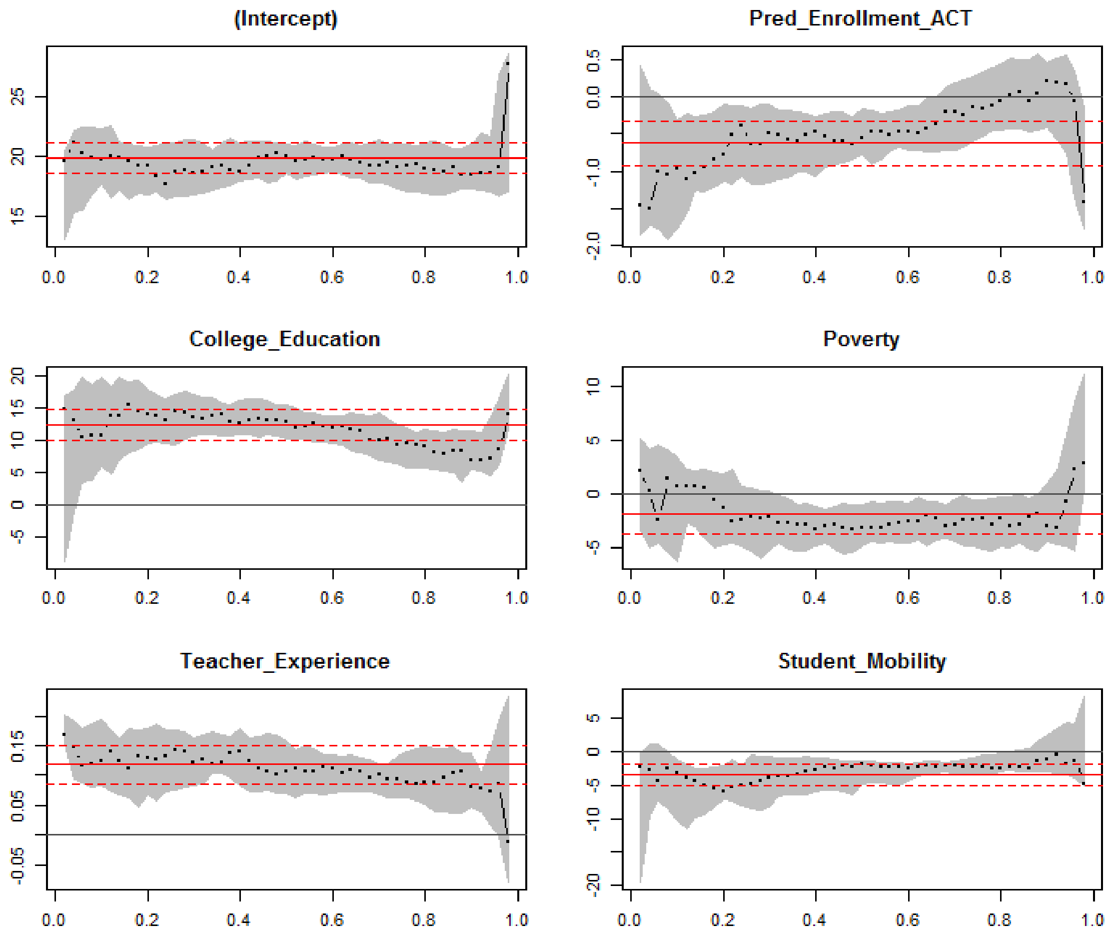


Figure 1-5 2SLAD quantile regression covariates effects for average ACT

REFERENCES

Angrist, J.D., and A.B. Krueger. 2001. Instrumental Variables and the Search for Identification: from Supply and Demand to Natural Experiments. *Journal of Economic Perspectives* 15(4): 69-87.

Angrist, J.D., and V. Lavy. 1999. Using Maimonides' Rule to Estimate the Effect of Class Size on Scholastic Achievement. *The Quarterly Journal of Economics* 114(2): 533-575.

Barnett, R.R., C. Glass, R.I. Snowdon, and K.S. Stringer. 2002. Size, performance and effectiveness: Cost-constrained measures of best-practice performance and secondary-school size. *Education Economics* 10: 291–310.

Bivand, R.S., J. Hauke, and T. Kossowski. 2013. Computing the Jacobian in Gaussian spatial autoregressive models: An illustrated comparison of available methods. *Geographical Analysis* 45(2): 150-179.

Bivand, R.S., E. Pebesma, and V. Gomez-Rubio. 2013. Applied spatial data analysis with R, Second edition. Springer, NY. http://www.asdar-book.org/

Bivand, R.S., and P. Gianfranco. 2015. Comparing Implementations of Estimation Methods for Spatial Econometrics. *Journal of Statistical Software* 63(18): 1-36. URL http://www.jstatsoft.org/v63/i18/.

Bradley, S., and J. Taylor. 1998. The effect of school size on exam performance in secondary schools. *Oxford Bulletin of Economics and Statistics* 60: 291–324.

Brasington, D.M. 2007. Public- and Private-School Competition: The Spatial Education Production Function. In: Time and Space in Economics. Edited by Asada, T., and T. Ishikawa, pp 175-204.

Cohn, E. 1968. Economies of Scale in Iowa High School Operations. *Journal of Human Resources* 3(4): 422-434.

Crowder, K., and S.J. South. 2011. Spatial and temporal dimensions of neighborhood effects on high school graduation, *Social Science Research* 40(1): 87–106.

Eide, E., and M.H. Showalter. 1998. The effect of school quality on student performance: A quantile regression approach. *Economics Letters* 58: 345-350.

Elhorst, J.P. 2010. Applied Spatial Econometrics: Raising the Bar. *Spatial Economic Analysis* 5(1): 9-28.

Fan, X., and M. Chen. 2001. Parental involvement and students' academic achievement: A meta-analysis. *Educational Psychology Review* 13: 1–22.

Fowler-Finn, T. 2001. Student stability vs. mobility. *School Administrator* 58: 36–40.

Giraudoux, P. 2017. pgirmess: Data Analysis in Ecology. R package version 1.6.7. https://CRAN.R-project.org/package=pgirmess.

Greene, W.H. 2005. Econometric Analysis: 6th edition. Upper Saddle River, NJ. Pearson Prentice Hall.
Greenwald, R., L.V. Hedges, and R.D. Laine. 1996. The Effect of School Resources on Student Achievement. *Review of Educational Research* 66(3): 361-396.
Hanushek, E.A., P.E. Peterson, and L. Woessmann. 2014. U.S. Students from Educated Families Lag in International Tests. *Education Next* 14(4): 8-18.
Harris, D.N. 2006. Class Size and School Size: Taking the Trade-Offs Seriously. *Brookings Papers on Education Policy* 9: 137-161.
Hoagland, J.P. 1995. The effect of high school size on student achievement as measured by the California Assessment Program. Unpublished doctoral dissertation, University of LaVerne, Claremont.
Hoxby, M.C. 2000. The effects of class size and composition on student achievement: new evidence from natural population variation. *Quarterly Journal of Economics*: pp. 1239-1285
Humlum, M.K., and N. Smith. 2015. Long-term effects of school size on students' outcomes. *Economics of Education Review* 45: 28-43.
Huntsinger, C.S., and P.E. Jose. 2009. Parental involvement in children's schooling: Different meanings in different cultures. *Early Childhood Research Quarterly* 204: 398-410.
Izzo, C.V., R.P. Weissberg, W.J. Kasprow, and M. Fendrich. 1999. A longitudinal assessment of teacher perceptions and parent involvement in children's education and school performance. *American Journal of Community Psychology* 27: 817–839.
Jacques, C., B. Brorsen, and F. Richter. 2000. Consolidating Rural School Districts: Potential Savings and Effects on Student Achievement. *Journal of Agricultural Economics* 32(3): 573-583.
Jacques, C., and B. Brorsen. 2002. Relationship between types of school district expenditures and student performance. *Applied Economics Letters* 9: 997-1002.
Jeynes, W.H. 2007. The Relationship between Parental Involvement and Urban Secondary School Student Academic Achievement. *Urban Education* 42(1): 82-110.
Kahle, D., and H. Wickham. 2013. ggmap: Spatial Visualization with ggplot2. The R Journal, 5(1), 144-161. URL http://journal.r-project.org/archive/2013-1/kahle-wickham.pdf
Kenny, L.W. 1982. Economies of Scale in Schooling. *Economics of Education Review* 2(1): 1-24.
Kim, T.H., and C. Muller. 2004. Two-Stage Quantile Regression when the First Stage is Based on Quantile Regression. *Econometrics Journal* 7: 218-231.
Koenker, R., and G. Bassett. 1978. Regression quantiles. *Econometrica* 46: 33-50.
Koenker, R. 2016. quantreg: Quantile Regression, R package version 5.29. Available from: https://CRAN.R-project.org/package=quantreg.
Kostov, P. 2009. A spatial quantile regression hedonic model of agricultural land prices. *Spatial Economic Analysis* 4(1): 53-72.
Kuziemko, I. 2006. Using shocks to school enrollment to estimate the effect of school size on student achievement. *Economics of Education Review* 25: 63–75.
Leithwood, K., and D. Jantzi, 2009. A Review of Empirical Evidence About School Size Effects: A Policy Perspective. *Review of Educational Research* 79(1): 464-490.
Levin, J. 2001. For whom the reductions count: A quantile regression analysis of class size and peer effects on scholastic achievement. *Empirical Economics* 26: 221-246.

Marlow, M. 2000. Spending, school structure, and public education quality. Evidence from California. *Economics of Education Review* 19: 89-106.

McMillen, D. 2013a. Quantile Regression for Spatial Data. Springer.

McMillen, D. 2013b. McSpatial: Nonparametric spatial data analysis. R package version 2.0. https://CRAN.R-project.org/package=McSpatial

Murnane, R.J., and J.B. Willett. 2011. Methods Matter: Improving Causal Inference in Educational and Social Science Research. Oxford University Press Inc., New York 10016.

Nieuwenhuis, J., and P. Hooimeijer. 2016. The association between neighborhoods and educational achievement, a systematic review and meta-analysis. *Journal of Housing and the Built Environment* 31: 321–347.

Parke, C.S., and G.Y. Kanyongo. 2012. Student attendance, mobility, and mathematics achievement in an urban school district. *Journal of Educational Research* 105(3): 161–175.

Pebesma, E.J., and R.S. Bivand. 2005. Classes and methods for spatial data in R. R News 5(2). https://cran.r-project.org/doc/Rnews/.

R core Team. 2017. R: A Language and Environment for Statistical Computing. Available at https://www.R-project.org/

Rivkin, S.G, E.A. Hanushek, and J.F. Kain. 2005. Teachers, Schools, and Academic Achievement. *Econometrica* 73(2): 417-458.

Schreiber, J. B. 2002. Institutional and student factors and their influence on advanced mathematics achievement. *Journal of Educational Research* 95: 274–286.

Stanca, L. 2006. The effects of attendance on academic performance: Panel data evidence for introductory microeconomics. *Journal of Economic Education* 37 (4): 251–66.

Stevenson, D., and D. Baker. 1987. The family–school relation and the child's school performance. *Child Development* 58: 1348–1357.

Stevenson, K.R. 2009. School Size and Its Relationship to Student Outcomes and School Climate: A Review and Analysis of Eight South California State-Wide Studies. National Clearinghouse for Educational Facilities, Washington, DC. Available from: http://files.eric.ed.gov/fulltext /ED495953.pdf.

Tan, E.T., and W.A. Goldberg. 2009. Parental school involvement in relation to children's grades and adaptation to school. *Journal of Applied Developmental Psychology* 30: 442-453.

Walsh, P. 2010. Is parental involvement lower at larger schools? *Economics of Education Review* 29: 959-970.

Webbink, D. 2005. Causal Effects in Education. *Journal of Economic Surveys* 19(4): 535-560.

Whitacre, B., and J. Taylor. 2016. Do Small Schools Perform Better or Worse? *Oklahoma Cooperative Extension Fact Sheets* AGEC-1061.

Zhang, L., and T. Leonard. 2014. Neighborhood impact of foreclosure: A quantile regression approach. *Regional Science and Urban Economics* 48: 133-143.

APPENDICES

Table 1-7 Results of the First-stage Model for Endogeneity of School Size

Dependent Variable	School Size
Constant	5.185***
	(0.779)
Percent Attending Parent-teacher Conference	**-0.327***
	(0.179)
Average Days Absent	**0.067*****
	(0.011)
Instructional Expenditures ($/ADM)	**0.220*****
	(0.068)
Student Support Services ($/ADM)	**-0.474*****
	(0.126)
College Education	6.386***
	(0.588)
Poverty	0.990
	(0.708)
Teacher Experience	0.017
	(0.013)
Student Mobility	-0.732
	(0.600)
R^2	0.341
N	424
F	26.79

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level. Standard errors are shown in parenthesis.

CHAPTER II

ESTIMATING SPATIAL HETEROGENEITY IN HAY YIELD RESPONSES TO WEATHER VARIATIONS IN OKLAHOMA

Abstract

Hay is an important field crop in the U.S., with over 54 million harvested acres in 2015. In many southern states, hay is an important input for cattle production, and reducing forage costs is crucial for improving the profitability of livestock operations. It is well known that crop yields and quality are significantly influenced by weather variations, which can have different impacts across geographical regions and over years. This study quantifies possible heterogeneous impacts in hay yield responses to weather variations in Oklahoma hay yield. The paper uses panel data on hay yield for Oklahoma's 77 counties from 1977 to 2007. The weather variables include temperature and precipitation. Four distinct econometric models are specified, each allowing for a different method of estimating the local effects of weather variations on hay yield in geographic regions. The models are then compared in terms of predicted error using a hold-out method. Results suggest that geographic variation does exist in hay's response to weather. Accordingly, it is important to model hay production within a framework that allows weather response parameters to vary. Hay producers can reduce their production risk by incorporating models that permit geographical variation in how the local climate impacts yields.

Introduction

Hay is an important field crop in the U.S. with a gross value of $16.8 billion and total harvested acres of 54.4 million in 2015 (USDA-NASS, 2015). Alfalfa is known to be the most valuable variety of hay. Hay is an important forage crop in Oklahoma as well. In addition to the leguminous alfalfa, there are other leguminous (such as cowpeas, clover, and soybeans) and non-leguminous (such as ryegrass, bermudagrass, fescue, lovegrass, orchardgrass, and wheat hay/straw) forage/pasture crops grown in Oklahoma (Arnall et al., 2017). Oklahoma Agricultural Statistics (issued by Oklahoma Department of Agriculture, Food and Forestry and USDA-NASS) indicate that as an aggregate crop grouping, hay ranks in the top five crops of Oklahoma in terms of annual dollar value of production in most years. Oklahoma is one of the top producers of non-alfalfa hay varieties.

Hay plays an important role as input in cattle production, and profitability of livestock operations can be improved by reducing the input costs associated with forage production and feeding (Redfearn, 2003). Better forage conditions help Oklahoma cattle producers to implement more aggressive cattle production and marketing plans; decisions to expand cattle production depends greatly on realistic forage production estimates (Peel, 2005). Many popular cattle market information sources such as cattlenetwork.com frequently carry news about hay inventories, weather impacts, and their implications for cattle producers. Given these spillover effects of hay production into the cattle market, there is a need to better understand the characteristics of yield and prices of the hay.

Hay production is known to be sensitive to weather conditions. For example, total hay production in Oklahoma dropped from 5.9 million tons in 2010 to 2.3 million tons in 2011 due to the extreme drought conditions in that year (USDA-NASS, 2013). In addition to quantity, the quality of hay is influenced by temperature and rainfall during the crop season. Adverse temperature fluctuations during the season leads to mixed pasture or hay; growth of hay slows down if rainfall is insufficient and subsoil moisture is inadequate (Redfearn, 2013). Rainfall in Oklahoma is characterized by a steep decline from eastern part of the state to the west (MESONET, 2017). Inconsistent Oklahoma rainfall impacts nitrogen availability to hay crops, creating conditions in which moisture is more limited than nitrogen (Arnall et al., 2017). In addition to inherent regional characteristics such as soil quality and irrigation systems associated with a farm, these weather variables influence crop yields. Hence, spatial attributes and weather variables are critical in determining crop yield. There have been numerous studies that predict crop yield conditional on climatic information, using agricultural simulation models, such as the Environmental Policy Integrated Climate (EPIC) model (Williams et al., 1984; Butterworth et al., 2010), as well as a variety of multiple regression models. Using a crop simulation model, Butterworth et al. (2010) found that climate change affects the production of oilseed and the impact of climate change varies across geographic regions in the United Kingdom. Though many studies have analyzed the effect of climate and climate change on crop yield fluctuations, there have not been many attempts to model fluctuations in hay production. Toa et al. (2016) found that changes in temperature have an impact on field crop yields and that the yield varies across China. Some studies found that the impact of temperature on corn yields varies for different geographic regions in the United States (Schlenker and Roberts, 2009; Cai, Yu, and Oppenheimer, 2014).

Finding ways to improve hay yield predictions has become even more important after the introduction of the pilot Rainfall Index - Annual Forage Insurance plan (RI-AF) by the USDA Risk Management Agency (USDA-RMA, 2013) in Oklahoma and other selected states starting in May 2013. Crop insurance aids growers in risk management; a higher subsidy premium applies in areas with higher risks and riskier crops (Goodwin, 2001). In general, there is a systemic risk associated with crop yields across individual policy owners. Spatial correlation of yield with weather patterns is closely associated with such systemic risks. The correlation between price and yield, and the spatial dimension associated with this must be taken into account while estimating risk in insurance (Goodwin, 2001). Given that rainfall is a critical factor in hay production, the RI-AF plan insures growers against rainfall shortages below long-term average rainfall levels.[13] The program does not use actual rainfall amounts, but instead calculates rainfall indices across gridded regions (USDA-RMA, 2017). Therefore, an accurate estimate of the relationships between hay yield, weather and spatial variables helps in determining an accurate appropriate premium rate.

There can be two types of spatial relationships associated with crop yield distribution. One is spatial *dependence*, which refers to the fact that one observation in a cross sectional sample is dependent on one or more neighboring observations (Anselin, 1988). Spatial dependence can serve as a surrogate for unobserved covariates that vary smoothly over the entire region of interest (Cressie, 1993). Measures of spatial dependence can be either "local" or "global", with global meaning that one parameter is taken to describe the dependence across the whole study area. The other type of spatial relationship is *heterogeneity* in observed variables across space. Here, the mean and variance of the observed variable are not stationary across space. If this heterogeneity in parameters is attributable to spatially varying characteristics (such as physical geography and cultural practices etc.), then allowing those parameters to vary across space is optimal modeling of such heterogeneity (Brunsdon, Fotheringham, and Charlton, 1996; Fotheringham, Brunsdon, and Charlton, 2002; Smit et al., 2015). Cai, Yu, and Oppenheimer (2014) note that research on spatial heterogeneity in crop yields is limited. However, given the importance of spatial variability of crop yields in determining insurance premiums, a global measure of spatial dependence is likely inappropriate. Moreover, a more detailed accounting of regional differences in crop yields and climate impacts would be useful to develop more appropriate policy measures, or responses to those measures. Therefore, our study models both

[13] This insurance is available for annual forage used for haying or grazing for livestock feed or fodder. The RI-AF is structured so that producers can insure a productivity factor based on the county average.

spatial dependence and spatial heterogeneity of hay yield in Oklahoma. For measuring spatial dependence, we first use the Moran's I statistic and test its statistical significance; and then to model both spatial dependence and spatial heterogeneity in hay yield we make use of four alternative specifications, i.e., a non-spatial fixed-effects model, spatial fixed-effects lag and error models, and geographically weighted regression (GWR).

Econometric Modeling of Oklahoma Hay Yield

Moran's I Statistics for Special Dependence

To measure spatial dependence in hay yield, we calculate Moran's I for each year in the panel to determine any patterns in spatial dependence over the years. Moran's I is a global indicator[14] of spatial autocorrelation, and the statistic can be used to test the hypothesis that the spatial process promoting the pattern of observations is due to random chance. If the statistic is positive and statistically significant, it implies that similar values of hay yields have spatially clustered pattern compared to a spatial process with random distribution. In contrast, a negative and statistically significant Moran's I -statistic indicates clustering of dissimilar hay yields. The value of Moran's I ranges from -1 to 1, with 0 suggesting no evidence of spatial clustering. Neighboring units can be defined in a variety of ways, including distance-based or contiguity. The Moran's I is calculated as follows (Cliff and Ord, 1981):

(10)
$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} {z_i}^2}$$

where n is the number of observations, w_{ij} is the spatial weight between locations i and j, $S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}$ is the aggregate of all spatial weights, and $z_i = (y_i - \bar{y})$ is the deviation of observed yield y from its mean. The variance of I is given by (Cliff and Ord, 1981):

[14] Spatial dependence measures that are based on simultaneous measurements from many locations are called global spatial statistics (Cliff and Ord, 1981).

$$Var_N(I) = \frac{1}{(n-1)(n+1)\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)^2}\left[n^2 S_1 - nS_2 + 3\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)^2\right] - \frac{1}{(n-1)^2}$$

where $S_1 = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left(w_{ij} + w_{ji}\right)^2, S_2 = \sum_{i=1}^{n}(w_i + w_i)^2$. The expected value of I is given by $E_N(I) = -(n-1)^{-1}$ and the statistical significance of I is given the Z-score computed as $Z = \frac{I - E(I)}{\sqrt{Var(I)}}$.

Non-spatial and Spatial County Fixed Effects

The basic econometric model is a linear regression model (the "pooled" model) estimated using ordinary least-squares (OLS), ignoring any spatial and temporal effects on hay yield. The pooled model is given as:

(11) $$y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 t + \epsilon_{it}$$

where y_{it} is the hay yield in county i at time t, X_{it} is a vector of weather variables (average temperature and precipitation) in county i at time t, t is a linear time trend that accounts for technological changes over time, β_0, β_1, and β_2 are parameters to be estimated, and ϵ_{it} is the disturbance term.[15]

The next model takes advantage of the panel structure of the data to estimate a fixed-effects regression model as follows:

(12) $$y_{it} = \beta_{0i} + \beta_1 X_{it} + \beta_2 t + \epsilon_{it}$$

where β_{0i} are coefficients of time-invariant fixed-effects on the geographical units estimated using the least-squares dummy variables (LSDV) estimator. In equation (3), it is possible to

[15] A first-differenced version of (2) can be used to estimate the time-invariant unobserved effects of individual components.

include time-specific fixed effects.[16] Since we have information about the geospatial location of the hay yield data, it is possible to improve model (3) by incorporating this spatial information. Therefore, a spatial fixed-effects model that includes both a spatial lag and a spatial error term is estimated as follows:

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \beta_0 + \beta_{0i} + \beta_1 X_{it} + \beta_2 t + \epsilon_{it} \tag{13a}$$

$$\epsilon_{it} = \lambda \sum_{j=1}^{N} w_{ij}\, \epsilon_{jt} + u_{it} \tag{4b}$$

where w_{ij} is an element in the spatial weight matrix W, and ρ and λ are the spatial autoregressive and autocorrelation coefficients, respectively. The spatial weight matrix is created from the latitude and longitude information of individual counties based on distance-based measures. All counties are considered neighbors but closer ones are given more weight.[17]

We can then test to find out which of these models is a better fit. We use the classic LM-tests and the robust LM-tests (Anselin, 1988; Anselin et al., 1996) to test whether the spatial lag or spatial error models are improvements to the basic OLS specification (i.e. $H_0: \rho = 0$ or $\lambda = 0$). Both tests are implemented based on the residuals of the OLS model and follow a Chi-squared distribution with one degree of freedom.

The log-likelihood function of (13a) is given as:

[16] Random-effects model is not suitable in this case due to the violation of the orthogonality condition of the spatial variables with the weather variables (Cai, Yu, and Oppenheimer, 2014).

[17] Alternatively, the spatial weight matrix will be defined using contiguity-based measures to check the robustness of model. The spatial weighted matrix used can vary from contiguity-based measures to distance-based ones.

(14)
$$LogL = -\frac{NT}{2}\log(2\pi\sigma^2) + Tlog|I_N - \rho W| - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it} - \rho\sum_{j=1}^{N} w_{ij}y_{jt} - \beta_0 - \beta_{0i} - \beta_1 X_{it} - \beta_2 t\right)^2$$

where the second term on the right hand side is the Jacobian term of the transformation from ϵ_{it} to y_{it} taking into account the endogeneity of $\sum_{j=1}^{N} w_{ij}y_{jt}$ (Anslin, 1988, P. 63). The partial derivatives of the log-likelihood with respect to β_{0i} are:

(15)
$$\frac{\partial LogL}{\partial \beta_{0i}} = \frac{1}{\sigma^2}\sum_{t=1}^{T}\left(y_{it} - \rho\sum_{j=1}^{N} w_{ij}y_{jt} - \beta_0 - \beta_{0i} - \beta_1 X_{it} - \beta_2 t\right) = 0, i = 1, \dots, N$$

whose solution is given by:

(16)
$$\beta_{0i} = \frac{1}{T}\sum_{t=1}^{T}\left(y_{it} - \rho\sum_{j=1}^{N} w_{ij}y_{jt} - \beta_0 - \beta_1 X_{it} - \beta_2 t\right) = 0, i = 1, \dots, N$$

Substituting the solution of β_{0i} from (16) into the log-likelihood function and rearranging the terms, the concentrated log-likelihood function is:

(17)
$$LogL = -\frac{NT}{2}\log(2\pi\sigma^2) + Tlog|I_N - \rho W| - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it}{}^{*} - \rho\left[\sum_{j=1}^{N} w_{ij}y_{jt}\right]^{*} - \beta_0 - \beta_1 X_{it}{}^{*} - \beta_2 t\right)^2$$

where the asterisk denotes demeaned variables, i.e., for a variable x_{it}, $\left(x_{it}{}^{*} - \sum_{t=1}^{T}\frac{x_{it}}{T}\right)$. Details of estimation of (4a) or (4b) are provided in Elhorst (2014, p. 37-93). The maximum likelihood estimates of ρ and (β, σ^2) are computed sequentially by fitting in the OLS estimates and residuals into the concentrated log-likelihood function.[18]

Geographically Weighted Regression

Regular spatial models such as the spatial lag model or spatial error model assume that coefficients are constant over space. As an alternative, we use the GWR, which is a special case of locally weighted regression, as a flexible model of spatial heterogeneity in crop yield response. In a locally weighted regression, the conditional mean equation is given by $y = XB(z)$ where X can be any variables and z are the variables that enter non-parametrically. In GWR, the z variables are coordinates of the geographical unit (McMillen, 2013). Econometric specification of GWR is as follows:

(18) $$y_{it} = \beta_{0i} + \beta_{1i}X_{it} + \epsilon_{it}$$

where the i component is defined by the latitude and longitude of the respective county. The difference between (9) and (3) is that the former allows the X_{it} variables to have spatially varying impact on crop yield response as denoted by β_{1i}. In the locally weighted regression, coefficients are calibrated by assigning weights to data points at locations according to their spatial proximity to location i. These weights allow the nearer spatial points to have greater influence on the yield response than the farther ones. Parameters of (9) are obtained by minimizing a weighted residual sum of squares. If (u, v) represents the latitude and longitude of spatial unit i, the regression coefficients (say $\hat{\beta}$) are given by:

$$\hat{\beta}(u, v) = (X^T W(u, v) X)^{-1} X^T W(u, v) y$$

[18] We used different packages available in the open-source software *R* (R Core Team, 2017) for data preparation and analysis. The packages used are “ggmap” (Kahle and Wickham, 2013); “plm” (Croissant and Millo, 2008); “sp” (Pebesma and Bivand, 2005; Bivand, Pebesma, and Gomez-Rubio, 2013); “pgirmess” (Giraudoux, 2017); “spdep” (Bivand and Piras, 2015); and “splm” (Millo and Piras, 2012).

where

$$W(u,v) = \begin{bmatrix} w_1(u,v) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_n(u,v) \end{bmatrix}$$

with the elements of the $W(u,v)$ calculated by kernels. A Gaussian kernel shape is given by

$$w_i(u,v) = e^{-0.5\left(\frac{d_i(u,v)}{h}\right)^2}$$

where $d_i(u,v)$ is the Euclidean distance between location (u,v) and observation i, and h is the bandwidth (a quantity expressed in the same coordinate units as used in the data). Other types of kernel shapes may be used to define the $W(u,v)$ matrix. Even though the type of kernel shape does not influence the results of regression, the choice of bandwidth may be of critical importance. For larger values of h, the weights $w_i(u,v)$ tend to one and the estimation results would be similar to those using OLS. When the sample is regularly spaced in the study area, a kernel with fixed bandwidth is recommended. If this is not the case, an adaptive bandwidth may be the solution. In the adaptive form, a minimum number of observations or a maximum distance are fixed in order to calculate the weights (Suarez-Vega et al, 2013, p. 195-212). To estimate the GWR model, the "spgwr" package in R is used (Bivand and Yu, 2013). The fixed effects within this model specification are estimated by demeaning crop yield and weather variables.

Holdout Method for Model Selection

A Cross-validation (CV) technique is used to evaluate how accurately a predictive model performs on new data. Particularly, the holdout method, which is the simplest kind of cross validation is used to determine which model performs the best to the data out of sample. We first split the original data into two sets, as a training data set and a testing data set. Each model specified is estimated on the training data and tested on the testing data based on prediction performance. To evaluate which model provides the best out-of-sample fit, we need a measurement to compare models. Root mean squared error (RMSE) and mean absolute percentage error (MAPE) are used to evaluate predictive accuracy, which are defined as:

(10) $$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$$

(11) $$MAPE = \frac{100\%}{n}\sum_{n=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|.$$

Data

We pooled county level hay production data from the annual reports of Oklahoma Agricultural Statistics for the period of 1977–2007.[19] These reports contain estimates of acreage, production quantity, and yield for hay crops. Data on hay are available for three different levels of crop aggregation: only alfalfa, non-alfalfa (grouped together as "other" hay), and all hay (sum of alfalfa and the "other"). The data on all hay production has a balanced panel structure comprising of 77 counties (belonging to nine geographical districts) and 31 years.[20] The box plots of county level all hay yield as well as hay yield aggregates for each year are presented in Figures 1 and 2. Spatial variations in average Oklahoma hay yield is presented in Figure 3.

Daily weather data were obtained from Schlenker (2017). The data is available at www.wolfram-schlenker.com/dailyData.html. The data contains daily precipitation, and daily minimum and maximum temperatures on a 2.5 x 2.5 mile grid for the contiguous Oklahoma state. First, we created daily average temperature for each grid by taking the average of minimum and maximum temperatures. We then converted daily average temperature and precipitation on 2.5 x

[19] These reports provide information on the rank of hay crops within the crop portfolio of Oklahoma, and also the rank of Oklahoma hay production in the U.S. The reports also provide a snapshot of weather for the year of reporting and how those weather conditions affected different crops.
[20] Hay yields data used in this study were limited to the period of 1977–2007 in order to include all counties in Oklahoma while maintaining a balanced panel. During 2008–2015, some counties did not publish any data, or were combined with a smaller county.

2.5 mile grids to county-level data by taking the average of all grid observations corresponding to each county. Finally, we converted daily county-level data to monthly county-level data by taking the average of daily observations for each month in a county. Seasonal average temperature and precipitation are calculated by taking the average of monthly observations for each season in a county. S1 is the average of the winter months' observations from January to March, S2 is the average of the spring months from April to June, S3 is the average of the summer months from July to September, and S4 represents the average of the fall months from October to December, respectively. We hypothesize that the spring and summer seasons (S2 and S3) are the most important for hay production and that temperature and precipitation have different impacts on hay yield depending on the geographic region within Oklahoma. Maples *et al.* (2016) has already described how that lack of precipitation was not necessarily correlated with decreased hay yield, for one location in Oklahoma. The summary statistics for all hay yield, seasonal mean temperatures, and seasonal total precipitations are presented in Table 1. The average of all hay yield of all counties in Oklahoma over the period of 1977–2007 is 1.92 tons per acre. Temperature and precipitation have significant fluctuations by county, but on average the hottest season is the summer (S3), and the wettest is the spring (S2) (as expected).

Results

We first test for the potential spatial autocorrelation of hay yield among neighboring counties in Oklahoma during the period of 1977–2007. The results from the Moran's *I* statistics and the corresponding *p*-values for the statistics are reported in Table 2. With the exception of four years, we find a strong positive spatial autocorrelation of hay yield among counties in Oklahoma during the period of 1977–2007, although the Moran's *I* values are not extremely large (Wall, 2004). We then implement the local Moran's *I* statistic to see if spatial autocorrelation of all hay yield is present among a subset of counties in Oklahoma. The results from the local Moran's *I* statistics and the corresponding *p*-values for the statistics are illustrated in Figures 4 and 5, respectively.

We see that there are several counties which show significant local autocorrelation in hay production. Clusters of counties with high levels of hay production can be found in the Oklahoma panhandle and on the north and south west parts of Oklahoma, while the east central part shows a significant clustering of counties with low production.

The results from the fixed effects and spatial fixed effects lag and error models with a linear time trend using panel data, and the GWR model using the 31-year averaged data are presented in Table 3. The estimation results from the fixed effects model show negative impacts associated with temperature and positive impacts for precipitation in each of the 4 seasons as expected. After controlling for these variables, there are significant positive (and negative) county fixed effects, and a significant negative time trend. The coefficient estimates for the county fixed effects are presented in Table 5 and the spatial distribution of their coefficients is illustrated in Figure 6. The results also find that hay yield is negatively associated with seasonal mean temperatures while positively associated with seasonal total precipitations.

We implement the Moran's *I* test on the residuals of the non-spatial fixed effects model for the existence of spatial correlation in the residuals. The results are presented in Table 4. We found significant spatial dependence in seventeen of the thirty-one (55%) years. In those years in which spatial dependence is not present, the county-level fixed effects parameters might capture the geographical variation in the data. Alternatively, we used panel versions of the standard LM-test and the locally robust LM-test to test for the potential spatial dependence on county-level hay yield. For spatial lag dependence, the results of both tests suggest that there is significant spatial dependence between neighboring county hay yields, with the standard LM test and locally robust LM test statistics of 373.02 and 21.47, respectively, with the corresponding *p*-values less than 0.001. For spatial error dependence, the standard LM test and locally robust LM test statistics are 354.40 and 2.85 and their corresponding *p*-values are less than 0.001 and 0.10, respectively, indicating a county's unobserved factors are correlated with those of neighboring counties.

In the spatial fixed effects models, significant spatial lag and error effects at the 5% level were found in hay production. In particular, the spatial lag and error coefficient estimates (ρ and λ) are 0.425 and 0.435, respectively, suggesting not only that hay yield depends on neighboring counties' hay yields, but also that there is spatial correlation between the errors. The reason we don't specify a model with both ρ and λ is that it is difficult to interpret and is overparameterized (Elhorst and Vega, 2013). The spatial lag model has results in about 17% of counties with significant fixed effects, while the spatial error model has only about 26% of counties with significant fixed effects (reinforcing our finding from the Moran's *I* of the residuals for the non-spatial model). The coefficient estimates for the county fixed effects from both models are presented in Table 5 and the spatial distributions of their coefficients are illustrated in Figures 7 and 8, respectively. The results from both the spatial fixed effects lag and error models find that hay yield is negatively related to mean temperature. For total precipitation, both the spatial fixed effects lag and error models find that hay yield is positively related for three seasons. In both models, the association between total precipitation and hay yield during the winter season was statistically insignificant. In most cases, the coefficients from the spatial lag and error models are slightly lower in values when compared to those for the non-spatial fixed effects model.

As another method to examine spatial heterogeneity in hay yield responses to weather variations, the GWR model is estimated. The optimized bandwidth selected by a Cross Validation (CV) criterion with adaptive bandwidths is used for the GWR local model and for each local model is estimated with 46 observations. The coefficient estimates of the GWR model show certain spatial variability in hay yield responses to weather variations in Oklahoma (Table 3). In particular, hay yield is positively associated with spring season temperature on the central and southcentral parts of Oklahoma, while the negative relationships are found on other parts of Oklahoma (Figure 9b). In terms of winter season total precipitation, hay yield is negatively associated with precipitation in eastern Oklahoma and a portion of the west central regions of

Oklahoma, and positively correlated with central and a small portion of western Oklahoma (Figure 10a). The coefficients for spring season mean temperature range from a minimum value of -0.128, where a 1 ºC increase in temperature results in a drop in average hay yield by 0.128 tons per acre, to 0.109, where a 1 ºC increase in temperature results in an increase in average hay yield by 0.109 tons per acre. The coefficient estimates for winter season precipitation range from -0.157 to 0.185. The estimation results from the GWR model found some evidence of spatial varying relationship between weather and hay yield, suggesting that weather impacts on hay yield varies across geographic regions of Oklahoma.

Out-of-sample Prediction

The holdout method is used to investigate the performance of the GWR model and to determine which model performs the best to predict hay yield responses to weather variations among four alternative models (i.e., the fixed-effects model, spatial fixed-effects lag and error models, and GWR model). Specifically, the data are split into a training data set, the first 26 years of observations (1977–2002), and a testing data set, the last five years of observations (2003–2007). We estimate the models on the training data, and then calculate the out-of-sample RMSE and MAPE on the testing data to evaluate which model provides the best out-of-sample fit based on their prediction accuracy.

The results for out-of-sample prediction accuracy are presented in Table 6. We find the fixed effects model (in 2005 and 2006) and spatial fixed effects lag model (in 2003, 2004, and 2007) perform better than the spatial fixed effects error and GWR models. In particular, the fixed effects model has the smallest RMSE of 0.343 (14% MAPE) in 2005 and 0.771 (74% MAPE) in 2006, while the spatial fixed effects lag model has the smallest RMSE of 0.342 (15% MAPE) in 2003, 0.310 (14% MAPE) in 2004, and 0.442 (14% MAPE) in 2007. We also find that the GWR model has relatively high prediction errors on the testing data, suggesting the GWR model may overfit the training data. Specifically, the adjusted R^2 value of the GWR model (0.52) is significantly larger than that of the fixed effects model (0.25) indicating that the GWR model fits the data better, as reported in Table 3. Interestingly, in 2006, the prediction errors of all models are more than doubled, indicating that there was larger variation of hay yield influenced by weather. In fact, hay yields in 2006 were the lowest in the 31-year study period examined (Figure 2).

Conclusion

The importance of hay yield prediction has increased with the introduction of the pilot RI-AF Insurance plan by the USDA Risk Management Agency in selected states, including Oklahoma, in May 2013. Accurate estimates of the relationship between weather and hay yield, and their spatial heterogeneity, are necessary to determine appropriate insurance premium rates. Based on a series of non-spatial and spatial analyses, this study examined the spatial dependence as well as spatial heterogeneity of hay yield, and the spatial variation of weather impacts on hay yield in Oklahoma during the period of 1977–2007. Specifically, four distinct models are tested that include varying methods for relationships between weather and hay yield.

We find that temperature tends to have a negative effect, while precipitation has a positive effect, on hay yield in Oklahoma. After controlling for weather impact on hay yield, there are significant positive (and negative) county fixed effects, and a negative time trend. The results from the spatial fixed effects lag model find that hay yield also depends on neighboring counties' hay yields, and results from the spatial fixed effects error model demonstrate that unobserved factors between neighboring counties are also positively correlated.

We also find that weather variation has different impacts on hay yield in different geographical regions. For example, spring season temperature has a positive effect on hay yield in the central and south central parts of Oklahoma, while it negatively affects hay yields in all other regions of Oklahoma. Similarly, winter season total precipitation has a negative effect on hay yield in the eastern and a portion of west central regions of Oklahoma, but a positive effect on hay yield in the central region of Oklahoma.

When compared to out-of-sample prediction accuracy among the four alternative models, the fixed effects model and spatial fixed effects lag model perform better than the spatial fixed effects error and GWR models. The GWR model may tend to overfit the data, suggesting that it is useful for exploring spatially varying relationships between various climate factors and hay yield. If there was larger variation of hay yield influenced by weather variations, prediction accuracy decreases significantly.

Our findings suggest that geographic variation does exist in the impact of weather on hay yield. Accordingly, it is important to model hay production within a framework that allows weather response parameters to vary. By incorporating models that permit geographical variation in how the local climate impacts yield, hay producers can reduce their production risk. Modeling the local relationships between climatic factors and hay yield to improve risk management systems allows policymakers to better create effective programs to mitigate the potential negative impacts of crop yield variability due to regional differences of climatic effects.

The RI-AF uses the rainfall index calculated from recent precipitation relative to the long-term average within a producer's respective grid. In this study, we predicted hay yield for each county by estimating the spatially varying relationships between weather and hay yield. Incorporation of temperature along with precipitation may improve the risk assessment for potential crop losses due to varying impacts of weather upon different geographical regions. The results of this study could be used for evaluating the effectiveness of the RI-AF program as a risk management tool to protect hay producers from their production risk.

This study examined all hay yield which includes both alfalfa and other hay. It is well known that different crops respond differently to climate factors. In addition, whether or not crop yield is irrigated or non-irrigated can have different impact on crop yields (Cai, Yu, and Oppenheimer, 2014; Doughty et. al., 2018; Ziolkowska, 2018). Irrigation data was not incorporated into this study because it is not readily available at the county level. Future research should not only consider whether hay yield is aggregated from alfalfa or other hay, but also consider whether hay is irrigated or not by incorporating geospatial information of irrigation practices and the amount of irrigation water used. Inclusion of these factors may better explain the spatially varying relationship between climate factors and hay yield, and potentially allow more accurate predictions of hay yield during extreme weather events.

Table 2-1 Summary Statistics of All Hay Yield, Temperature, and Precipitation

Variable	N	Mean	Std. Dev.	Min	Max
AllHayYield (tons/ac)	2387	1.92	0.51	0.50	4.97
Avg.Temperature_S1 (ºC)	2387	6.18	1.99	-0.40	10.95
Avg.Temperature_S2 (ºC)	2387	20.21	1.26	14.21	23.37
Avg.Temperature_S3 (ºC)	2387	26.00	1.25	21.61	29.78
Avg.Temperature_S4 (ºC)	2387	10.17	1.47	5.35	13.81
Tot.Precipitation_S1 (mm)	2387	1.95	0.94	0.17	6.25
Tot.Precipitation_S2 (mm)	2387	3.67	1.21	0.65	7.96
Tot.Precipitation_S3 (mm)	2387	2.58	1.05	0.38	6.53
Tot.Precipitation_S4 (mm)	2387	2.37	1.28	0.15	7.60

Table 2-2 Moran's *I* of Oklahoma All Hay Yield, 1977-2007

Year	Average Yield (tons/ac)	Moran's *I*	p-value
1977	1.988	0.174***	0.002
1978	1.856	0.198***	0.001
1979	2.130	0.110**	0.030
1980	1.481	0.271***	0.000
1981	2.013	0.114**	0.026
1982	2.134	0.153***	0.005
1983	1.960	0.029	0.259
1984	1.836	0.092*	0.052
1985	2.297	0.302***	0.000
1986	2.182	0.117**	0.020
1987	2.015	0.110**	0.029
1988	1.757	0.312***	0.000
1989	2.097	0.263***	0.000
1990	1.865	0.306***	0.000
1991	1.881	0.172***	0.002
1992	2.210	0.166***	0.003
1993	2.021	0.303***	0.000
1994	1.891	0.062	0.110
1995	1.951	0.203***	0.000
1996	1.895	0.390***	0.000
1997	2.038	0.260***	0.000
1998	1.526	0.242***	0.000
1999	1.976	0.163***	0.002
2000	1.944	0.143***	0.008
2001	1.604	0.279***	0.000
2002	1.908	0.164***	0.003
2003	1.894	0.010	0.359
2004	2.006	0.269***	0.000
2005	1.796	0.245***	0.000
2006	1.156	0.301***	0.000
2007	2.239	0.066	0.112

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level.

Table 2-3 Estimation Results for the Fixed Effects, Spatial Fixed Effects, and GWR Models in Oklahoma Counties, 1977-2007

Dependent Variable		Spatial Fixed Effects Model		GWR				
Hay Yield	**Fixed Effects Model**	**Spatial Fixed Effects Lag Model**	**Spatial Fixed Effects Error Model**	**Min**	**1st Qu.**	**Median**	**3rd Qu.**	**Max**
Constant		2.708**	5.178***	-2.327	3.927	4.539	5.840	8.671
		(1.336)	(0.241)					
Avg.Temperature_S1	-0.016***	-0.013***	-0.012	-0.087	-0.038	-0.023	-0.004	0.086
	(0.005)	(0.005)	(0.008)					
Avg.Temperature_S2	-0.051***	-0.032***	-0.059***	-0.128	-0.059	-0.027	0.019	0.109
	(0.008)	(0.008)	(0.012)					
Avg.Temperature_S3	-0.076***	-0.040***	-0.078***	-0.155	-0.113	-0.069	-0.048	0.018
	(0.008)	(0.008)	(0.012)					
Avg.Temperature_S4	-0.032***	-0.017**	-0.029**	-0.193	-0.094	-0.053	-0.011	0.113
	(0.008)	(0.007)	(0.012)					
Tot.Precipitation_S1	0.020**	0.012	0.006	-0.157	-0.060	-0.018	0.031	0.185
	(0.010)	(0.009)	(0.013)					
Tot.Precipitation_S2	0.090***	0.056***	0.068***	-0.098	0.047	0.085	0.114	0.194
	(0.007)	(0.007)	(0.009)					
Tot.Precipitation_S3	0.065***	0.049***	0.062***	-0.071	-0.012	0.025	0.058	0.198
	(0.009)	(0.008)	(0.011)					
Tot.Precipitation_S4	0.034***	0.026***	0.023**	-0.107	-0.021	-0.003	0.028	0.110
	(0.007)	(0.007)	(0.009)					
t	-0.008***	-0.005***	-0.009***					
	(0.001)	(0.004)	(0.001)					
ρ		0.425***						
		(0.024)						
λ			0.435***					
			(0.025)					
N	2387	2387	2387					
Number of Counties	77	77	77					
Number of Years	31	31	31					
Adj. R^2	0.25					0.52		

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level. Standard errors are shown in parenthesis.

Table 2-4 Moran's *I* of the Residuals of Fixed Effect Model, 1977-2007

Year	Average Yield (tons/ac)	Moran's *I*	p-value
1977	1.988	0.234***	0.000
1978	1.856	0.008	0.375
1979	2.130	-0.053	0.727
1980	1.481	0.101**	0.041
1981	2.013	-0.011	0.487
1982	2.134	0.142***	0.009
1983	1.960	0.144***	0.008
1984	1.836	0.130**	0.014
1985	2.297	0.360***	0.000
1986	2.182	0.069*	0.094
1987	2.015	0.077*	0.083
1988	1.757	0.133***	0.007
1989	2.097	0.115**	0.024
1990	1.865	0.225***	0.000
1991	1.881	-0.083	0.857
1992	2.210	0.069	0.105
1993	2.021	0.155***	0.005
1994	1.891	-0.003	0.438
1995	1.951	0.032	0.241
1996	1.895	0.301***	0.000
1997	2.038	0.055	0.149
1998	1.526	0.163***	0.004
1999	1.976	0.011	0.344
2000	1.944	-0.033	0.625
2001	1.604	-0.021	0.551
2002	1.908	0.233***	0.000
2003	1.894	-0.014	0.507
2004	2.006	0.126**	0.018
2005	1.796	0.009	0.368
2006	1.156	0.159***	0.004
2007	2.239	0.060	0.132

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level.

Table 2-5 Estimation Results for the Fixed Effects and Spatial Fixed Effects Models in Oklahoma Counties, 1977-2007

Depend. Var.	**Fixed Effects Model**		**Spatial Fixed Effects Lag Model**		**Spatial Fixed Effects Error Model**	
Hay Yield	**Estimate**	**P-value**	**Estimate**	**P-value**	**Estimate**	**P-value**
Adair	4.583***	0.000	-0.041	0.866	-0.245	0.316
Alfalfa	5.864***	0.000	0.858***	0.000	0.992***	0.000
Atoka	4.555***	0.000	-0.301	0.239	-0.274	0.286
Beaver	4.722***	0.000	-0.238	0.291	-0.191	0.397
Beckham	4.853***	0.000	-0.085	0.722	-0.039	0.872
Blaine	5.056***	0.000	0.047	0.846	0.179	0.459
Bryan	4.892***	0.000	-0.002	0.993	0.057	0.823
Caddo	5.147***	0.000	0.317	0.195	0.277	0.260
Canadian	5.306***	0.000	0.542**	0.026	0.439*	0.072
Carter	4.738***	0.000	-0.280	0.270	-0.119	0.640
Cherokee	4.474***	0.000	-0.348	0.160	-0.356	0.150
Choctaw	4.851***	0.000	-0.052	0.838	0.025	0.923
Cimarron	5.543***	0.000	0.650***	0.002	0.595***	0.005
Cleveland	4.886***	0.000	0.088	0.723	0.032	0.897
Coal	4.670***	0.000	-0.195	0.444	-0.165	0.518
Comanche	4.961***	0.000	-0.115	0.645	0.090	0.718
Cotton	5.025***	0.000	-0.095	0.709	0.154	0.546
Craig	4.211***	0.000	-0.499**	0.040	-0.626***	0.010
Creek	4.496***	0.000	-0.255	0.304	-0.350	0.160
Custer	5.210***	0.000	0.238	0.321	0.329	0.172
Delaware	4.601***	0.000	-0.049	0.840	-0.236	0.332
Dewey	4.774***	0.000	0.054	0.819	-0.111	0.639
Ellis	5.229***	0.000	0.374	0.102	0.327	0.153
Garfield	4.901***	0.000	0.107	0.663	0.037	0.879
Garvin	5.579***	0.000	0.775***	0.002	0.727***	0.004
Grady	5.615***	0.000	0.726***	0.003	0.753***	0.002
Grant	5.157***	0.000	0.304	0.210	0.294	0.227
Greer	5.498***	0.000	0.555**	0.024	0.612**	0.013
Harmon	5.372***	0.000	0.329	0.183	0.48*	0.052
Harper	4.965***	0.000	0.057	0.806	0.065	0.781
Haskell	4.549***	0.000	-0.211	0.407	-0.276	0.280
Hughes	4.594***	0.000	-0.215	0.392	-0.248	0.325
Jackson	5.139***	0.000	0.124	0.620	0.256	0.306
Jefferson	4.790***	0.000	-0.151	0.552	-0.076	0.765
Johnston	4.666***	0.000	-0.238	0.349	-0.176	0.491
Kay	4.800***	0.000	0.018	0.941	-0.056	0.821
Kingfisher	4.956***	0.000	0.065	0.790	0.088	0.719
Kiowa	5.207***	0.000	0.347	0.159	0.329	0.183
Latimer	4.353***	0.000	-0.452*	0.076	-0.462*	0.070
LeFlore	4.365***	0.000	-0.418*	0.097	-0.448*	0.075
Lincoln	4.820***	0.000	0.004	0.987	-0.032	0.899
Logan	4.776***	0.000	-0.113	0.650	-0.081	0.746
Love	4.857***	0.000	-0.161	0.529	-0.001	0.996
Major	5.005***	0.000	0.111	0.646	0.126	0.602
Marshall	4.858***	0.000	-0.053	0.835	0.015	0.954
Mayes	4.482***	0.000	-0.253	0.305	-0.357	0.148
McClain	5.465***	0.000	0.581**	0.020	0.611**	0.014
McCurtain	4.903***	0.000	0.117	0.644	0.089	0.727
McIntosh	4.616***	0.000	-0.180	0.477	-0.216	0.396
Murray	5.069***	0.000	0.124	0.621	0.220	0.383
Muskogee	4.577***	0.000	-0.162	0.518	-0.254	0.313
Noble	4.763***	0.000	-0.143	0.562	-0.093	0.707
Nowata	4.268***	0.000	-0.458*	0.060	-0.571**	0.019
Okfuskee	4.526***	0.000	-0.220	0.381	-0.313	0.214
Oklahoma	5.187***	0.000	0.304	0.218	0.329	0.185
Okmulgee	4.324***	0.000	-0.398	0.108	-0.517**	0.038
Osage	4.501***	0.000	-0.250	0.308	-0.342	0.165

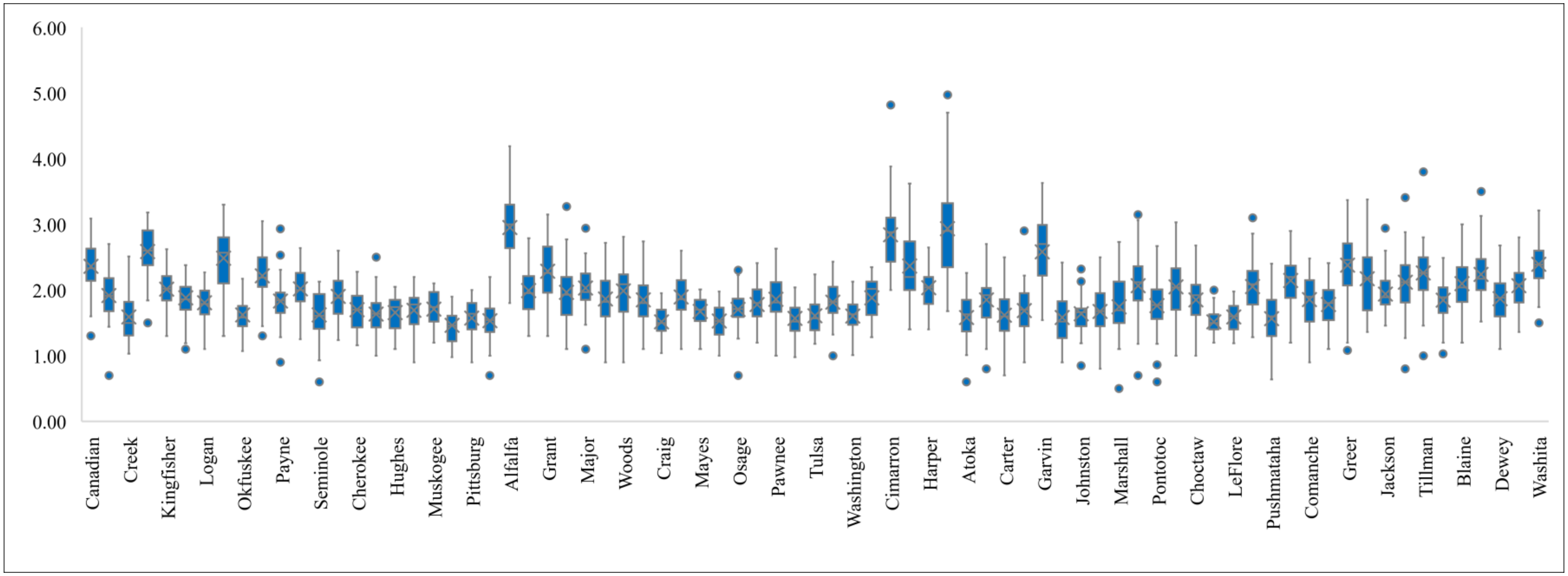
Table 2-5. Continued.

Depend. Var.	Fixed Effects Model		Spatial Fixed Effects Lag Model		Spatial Fixed Effects Error Model	
Hay Yield	**Estimate**	**P-value**	**Estimate**	**P-value**	**Estimate**	**P-value**
Ottawa	4.412***	0.000	-0.249	0.298	-0.425*	0.078
Pawnee	4.748***	0.000	-0.056	0.822	-0.100	0.688
Payne	4.740***	0.000	-0.083	0.736	-0.112	0.651
Pittsburg	4.503***	0.000	-0.346	0.174	-0.326	0.201
Pontotoc	4.701***	0.000	-0.094	0.706	-0.146	0.558
Pottawatomie	4.971***	0.000	0.159	0.524	0.122	0.627
Pushmataha	4.399***	0.000	-0.399	0.116	-0.416	0.102
RogerMills	4.994***	0.000	0.079	0.736	0.098	0.674
Rogers	4.374***	0.000	-0.359	0.145	-0.467*	0.059
Seminole	4.579***	0.000	-0.248	0.324	-0.267	0.289
Sequoyah	4.382***	0.000	-0.374	0.134	-0.446*	0.075
Stephens	5.140***	0.000	0.150	0.551	0.280	0.266
Texas	5.763***	0.000	0.821***	0.000	0.829***	0.000
Tillman	5.506***	0.000	0.362	0.153	0.629**	0.013
Tulsa	4.480***	0.000	-0.236	0.342	-0.363	0.145
Wagoner	4.686***	0.000	-0.069	0.784	-0.150	0.549
Washington	4.374***	0.000	-0.504**	0.039	-0.469*	0.055
Washita	5.415***	0.000	0.390	0.110	0.537**	0.028
Woods	4.922***	0.000	0.054	0.820	0.037	0.875
Woodward	4.744***	0.000	-0.181	0.436	-0.149	0.522

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level.

Table 2-6 Measures for Prediction Accuracy on the Testing Data

Models	Measurement Error	2003	2004	2005	2006	2007
Fixed Effects Model	RMSE	0.343	0.343	0.301	0.771	0.445
Spatial Fixed Effects Lag Model	RMSE	0.342	0.310	0.306	0.777	0.442
Spatial Fixed Effects Error Model	RMSE	0.350	0.340	0.315	0.779	0.488
GWR	RMSE	0.393	0.387	0.343	0.772	0.549
Fixed Effects Model	MAPE	15.227	16.438	13.909	73.612	15.064
Spatial Fixed Effects Lag Model	MAPE	15.030	14.448	14.389	74.303	14.469
Spatial Fixed Effects Error Model	MAPE	15.695	16.239	14.800	74.258	15.546
GWR	MAPE	17.156	17.085	16.178	74.479	18.773



Notes: These are organized so that neighboring counties are shown next to each other.

Figure 2-1 Box plot of county-level all hay yield (tons/ac) in Oklahoma, 1977-2007

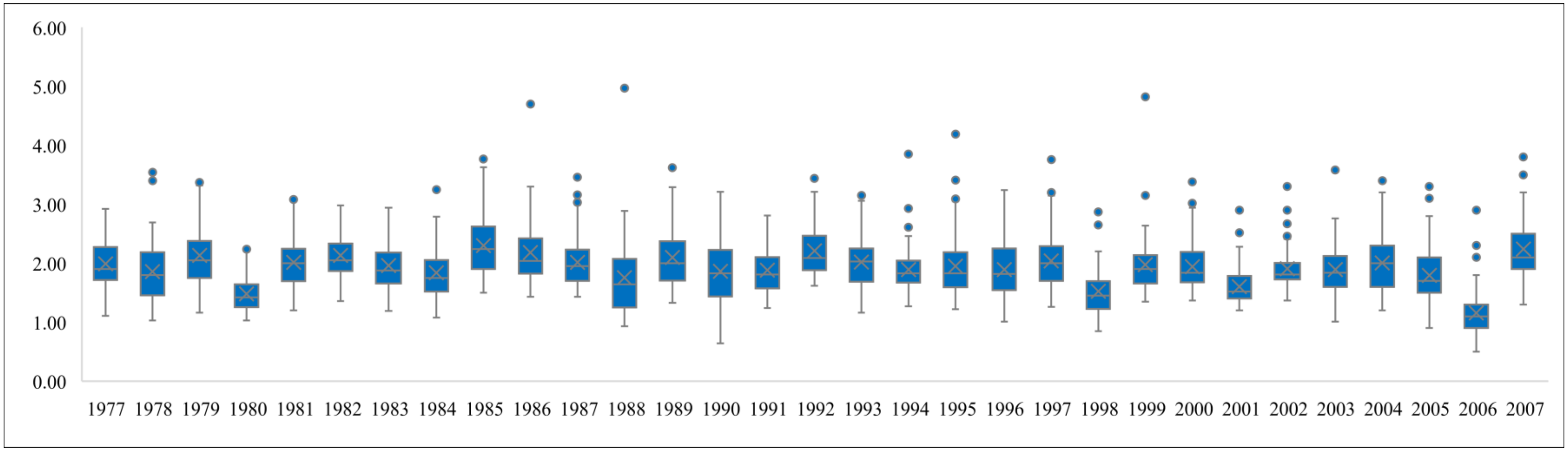


Figure 2-2 Box plot of yearly all hay yield (tons/ac) in Oklahoma, 1977-2007

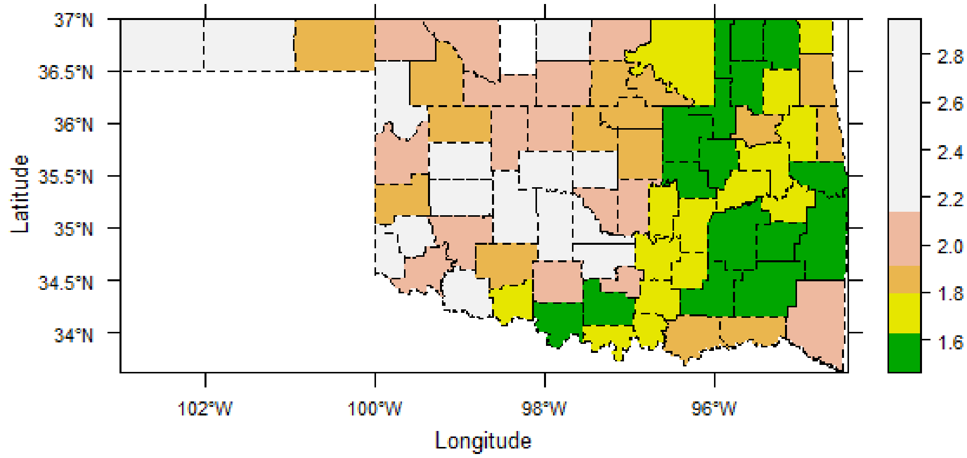


Figure 2-3 Spatial distribution of average all hay yield (tons/ac), 1977-2007

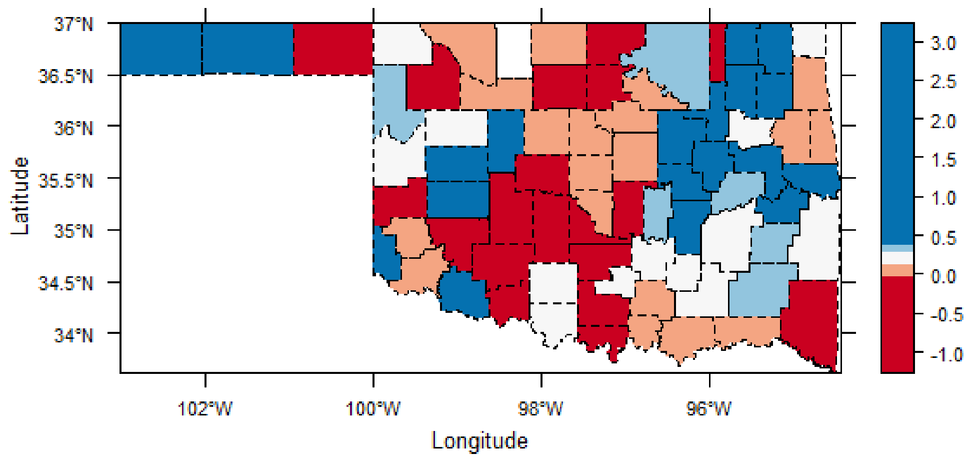


Figure 2-4 Spatial distribution of the local Moran's *I* statistics of average all hay yield

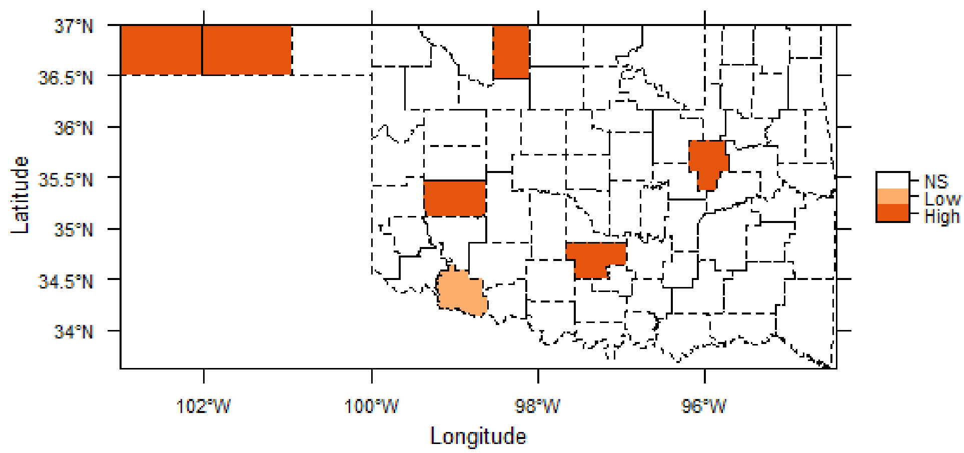


Figure 2-5 Spatial distribution of the significant local clusters of average all hay yield

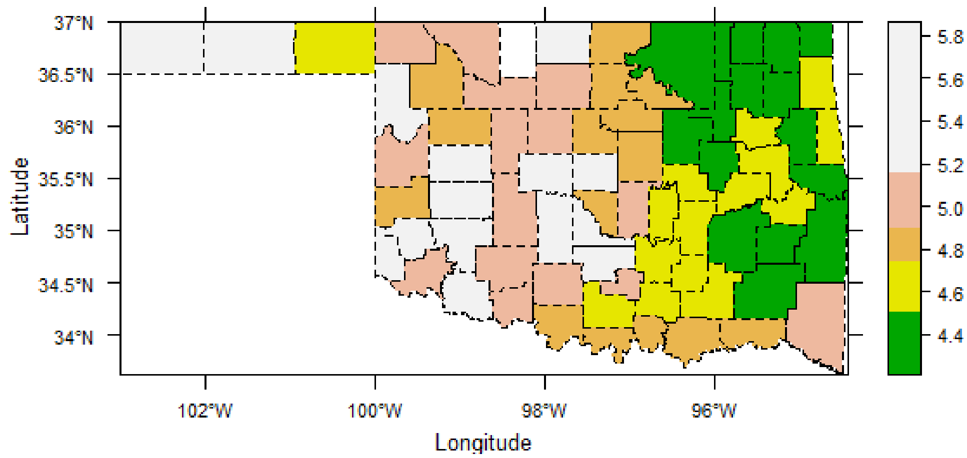


Figure 2-6 Spatial distribution of county fixed effects from the fixed effects model

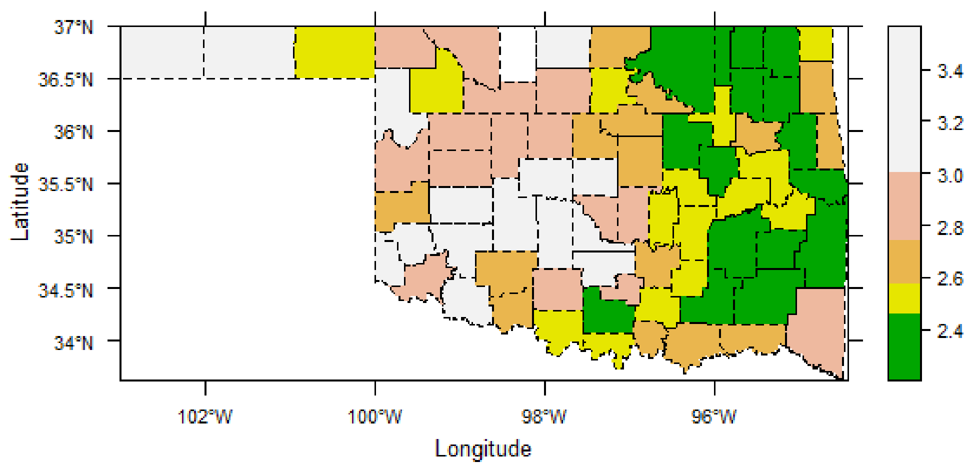


Figure 2-7 Spatial distribution of county fixed effects from the spatial fixed effects lag model

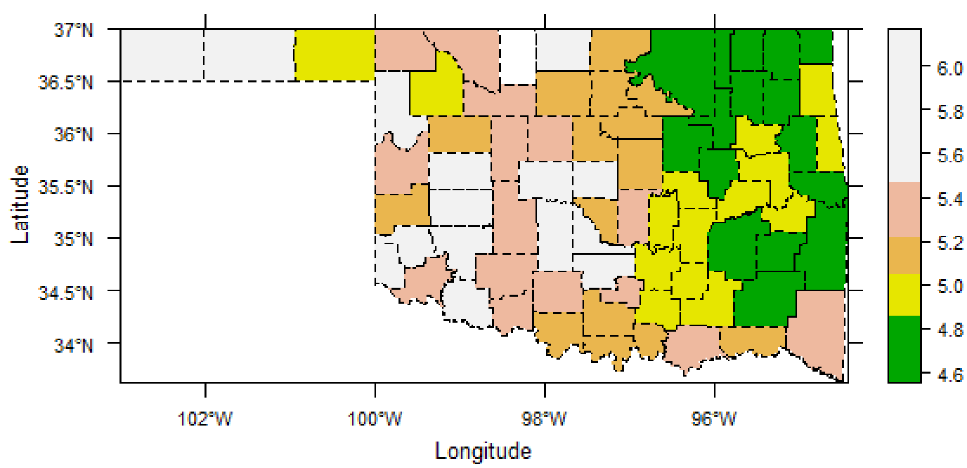


Figure 2-8 Spatial distribution of county fixed effects from the spatial fixed effects error model

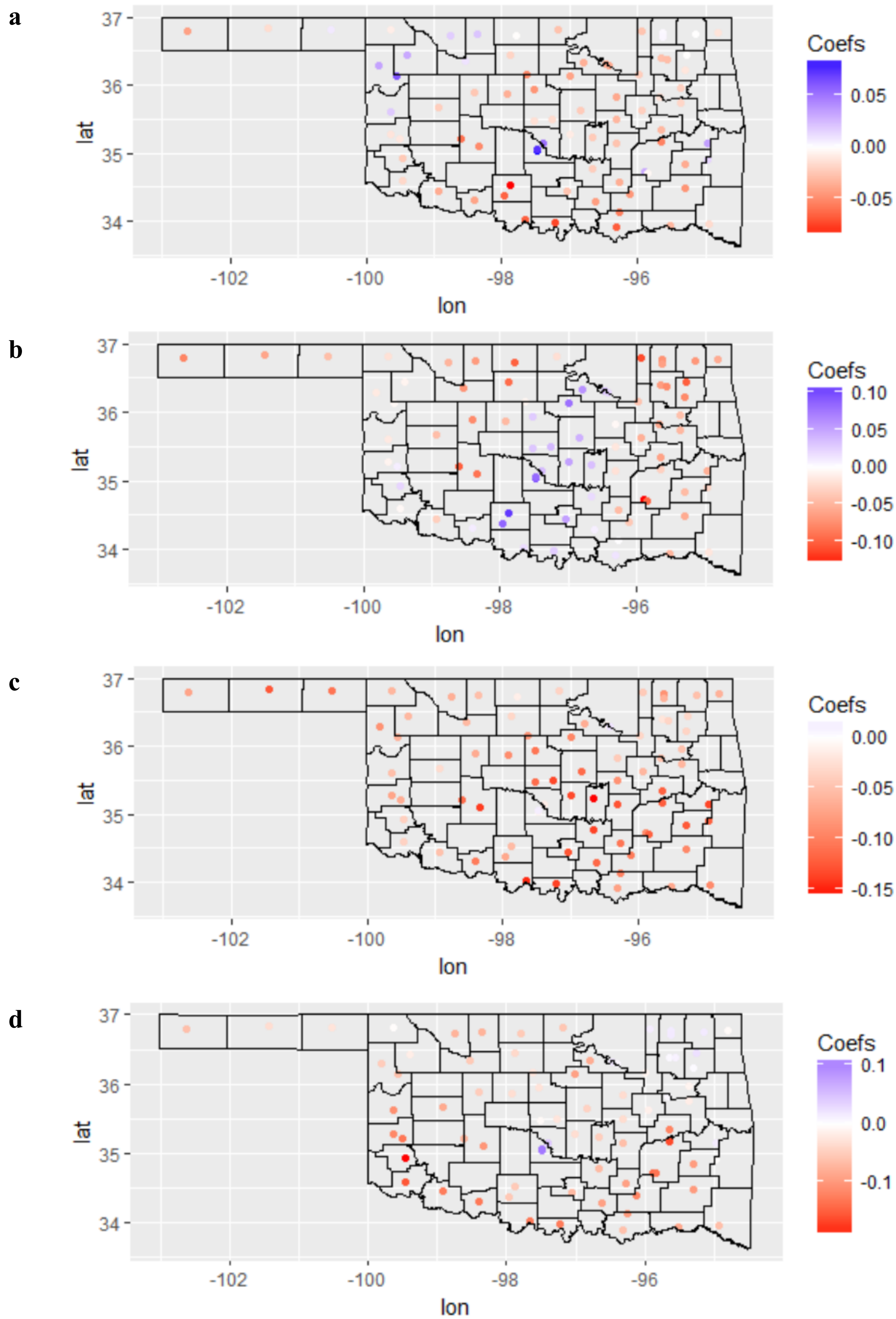
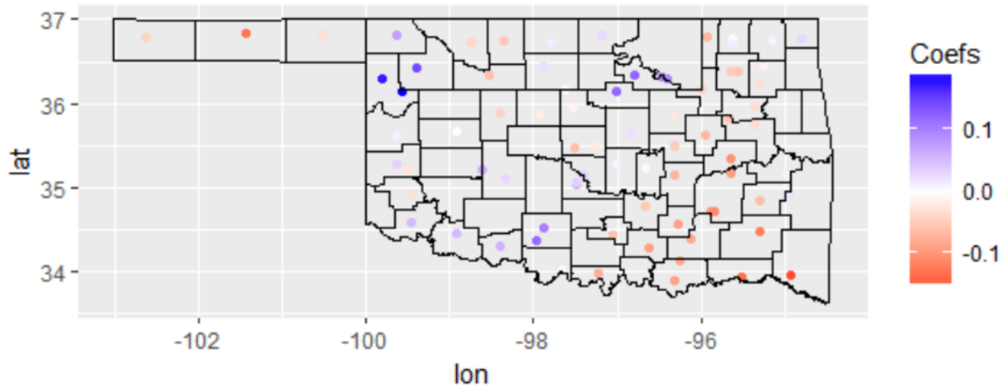
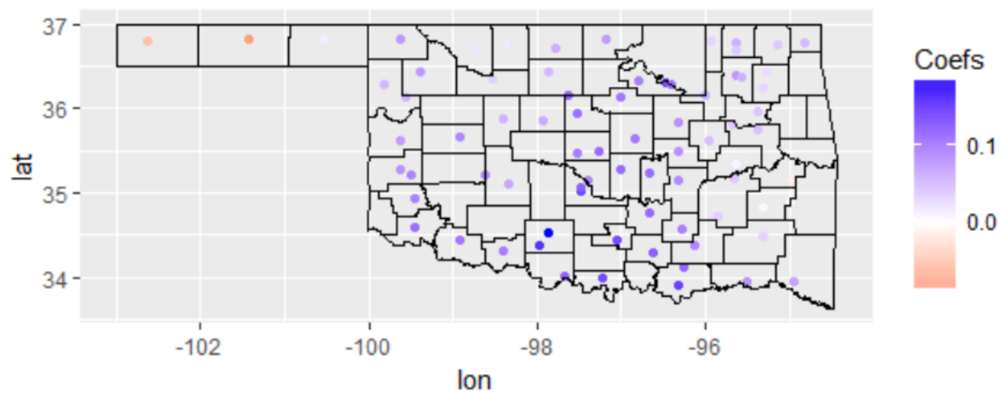


Figure 2-9 Spatial distribution of GWR coefficients of seasonal mean temperature effects

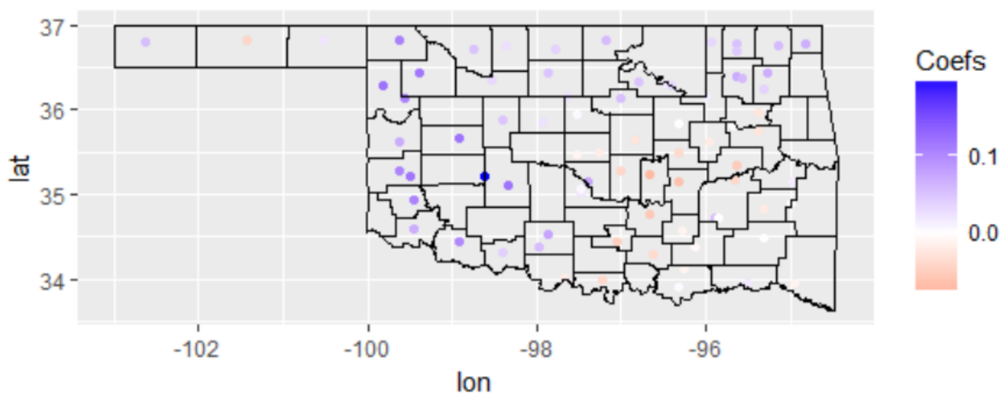
a



b



c



d

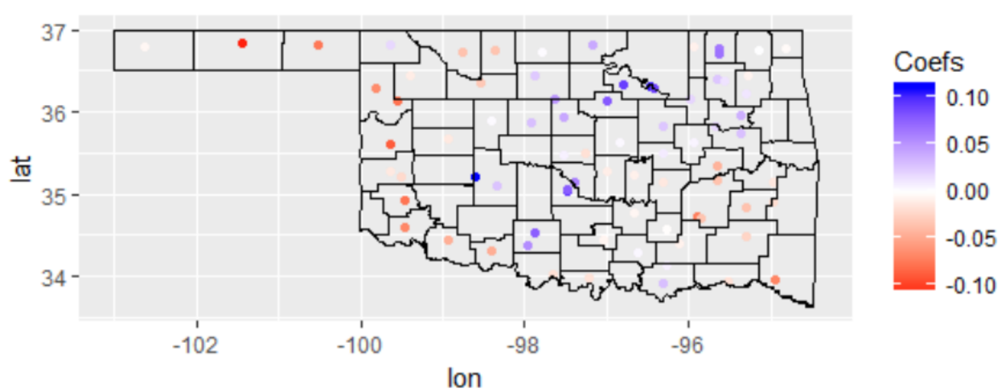


Figure 2-10 Spatial distribution of GWR coefficients of seasonal total precipitation

REFERENCES

Anselin, L. 1988. Spatial econometrics: methods and models. Dordrecht: Kluwer Academic Publishers.

Anselin, L., A.K. Bera, R. Florax, and M.J. Yoon. 1996. Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics* 26: 77-104.

Arnall, B., and D. Redfearn. 2017. Oklahoma Forage and Pasture Fertility Guide. Oklahoma Cooperative Extension Service Report E-1021.

Bivand, R., and D. Yu. 2013. "SPGWR - An R Package for Geographically Weighted Regression."

Bivand, R., and G. Piras. 2015. Comparing Implementations of Estimation Methods for Spatial Econometrics. *Journal of Statistical Software* 63(18): 1-36. URL http://www.jstatsoft.org/v63/i18/.

Bivand, R.S., E. Pebesma, and V. Gomez-Rubio. 2013. Applied spatial data analysis with R, Second edition. Springer, NY. http://www.asdar-book.org/

Brunsdon, C., A.S. Fotheringham, and M.E. Charlton. 1996. Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geographical Analysis* 28: 281–298.

Butterworth, M.H., M.A. Semenov, A. Barnes, D. Moran, J.S. West, and B.D.L. Fitt. 2010. "NorthSouth Divide: Contrasting Impacts of Climate Change on Crop Yields in Scotland and England." *Journal of the Royal Society Interface* 7: 123–130.

Cai, R., D. Yu, and M. Oppenheimer. 2014. Estimating the Spatially Varying Responses of Corn Yields to Weather Variations using Geographically Weighted Panel Regression. *Journal of Agricultural and Resource Economics* 39(2): 230-252.

Cliff, A.D., and J.K. Ord. 1981. Spatial Processes. Pion, London, UK pp. 266.

Cressie, N. 1993. Statistics for Spatial Data. John Wiley & Sons. New York.

Croissant, Y., and G. Millo. 2008. Panel Data Econometrics in R: The plm Package. *Journal of Statistical Software* 27(2). URL http://www.jstatsoft.org/v27/i02/.

Doughty, R., X. Xiao, X. Wu, Y. Zhang, R. Bajgain, Y. Zhou,…, J. Steiner. 2018. Responses of gross primary production of grasslands and crop lands under drought, pluvial, and irrigation conditions during 2010–2016, Oklahoma, USA. *Agricultural Water Management* 204: 47–59. https://doi.org/10.1016/j.agwat.2018.04.001.

Elhorst J.P., and S.H. Vega. 2013. On spatial econometric models, spillover effects, and W. ERSA Conference Papers No. ersa13p222. Available at http://www-sre.wu.ac.at/ersa/ersaconfs/ersa13/ERSA2013_paper_00222.pdf.

Elhorst, J.P. 2014. Spatial Econometrics: From Cross-Sectional Data to Spatial Panels. SpringerBriefs in Regional Science, Springer Publishers.

Fotheringham, A.S., C. Brunsdon, and M. Charlton. 2002. Geographically Weighted Regression: The Analysis of Spatially Varying Relationships. Chichester, West Sussex: Wiley.

Giraudoux, G. 2017. pgirmess: Data Analysis in Ecology. R package version 1.6.7.
https://CRAN.R-project.org/package=pgirmess.

Goodwin, B.K. 2001. Problems with Market Insurance in Agriculture. *American Journal of Agricultural Economics* 83(3): 643-649.

Kahle, D., and H. Wickham. 2013. ggmap: Spatial Visualization with ggplot2. *The R Journal* 5(1): 144-161. URL http://journal.r-project.org/archive/2013-1/kahle-wickham.pdf

Maples, J.G., B.W. Brorsen, and J.T. Biermacher. 2016. The Rainfall Index Annual Forage Pilot Program as a Risk Management Tool for Cool-Season Forage. *Journal of Agricultural and Applied Economics* 48(1): 29–51.

McMillen, D. 2013. McSpatial: Nonparametric spatial data analysis. R package version 2.0. https://CRAN.R-project.org/package=McSpatial.

MESONET. 2017. *Mesonet Rainfall by Month Table*. Retrieved from https://www.mesonet.org/index.php/weather/monthly_rainfall_table

Millo, G., and G. Piras. 2012. Splm: Spatial Panel Data Models in R. *Journal of Statistical Software* 47(1): 1-38. URL http://www.jstatsoft.org/v47/i01/

Oklahoma Forage and Pasture Fertility Guide. E-1021. Oklahoma Cooperative Extension Service. Division of Agricultural Sciences and Natural Resources. Available online: http://npk.okstate.edu/documentation/factsheets/Pasutre%20Handbook/E-1021web.pdf.

Pebesma, E.J., and R.S. Bivand. 2005. Classes and methods for spatial data in R. *R News 5* (2). Retrieved from https://cran.r-project.org/doc/Rnews/

Peel, D.S. (July 2015). Oklahoma hay and pasture situation. Retrieved from http://www.cattlenetwork.com/advice-and-tips/pasture-and-rangeland/oklahoma-hay-and-pasture-situation/

R Core Team. 2017. R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria. URL https://www.R-project.org/

Redfearn, D.D. (Summer 2013). Equine News. Oklahoma Cooperative Extension Service. Division of Agricultural Sciences and Natural Resources. Available online: from https://shareok.org/

Redfearn, D.D. 2003. Reducing Winter Feeding Costs. *Oklahoma Cooperative Extension Fact sheets* Pss-2057

Schlenker, W., and M.J. Roberts. 2009. Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change. *Proceedings of the National Academy of Sciences of the United States of America* 106 (37): 15594–15598.

Schlenker, W. 2017. Daily Weather Data for Contiguous United States (1950-2015). Available at: http://www.wolfram-schlenker.com/dailyData.html.

Smit, M.J., E.S. van Leeuwen, R.J.G.M Florax, and H.L.F. de Groot. 2015. Rural development funding and agricultural labour productivity: A spatial analysis of the European Union at the NUTS2 level. *Ecological Indicators* 59: 6-18.

Suarez-Vega, R., E. Acosta-Gonzalez, L. Casimiro-Reina, and J.M. Hernandez. 2013. Assessing the Spatial and Environmental Characteristics of Rural Tourism Lodging Units Using a Geographical Weighted Regression Model. In: Quantitative Methods in Tourism Economics. Springer-Verlag Berlin Heidelberg.

U.S. Department of Agricultural, National Agricultural Statistics Service. 2013. *2013 annual report*. Retrieved from https://www.nass.usda.gov/Publications/Ag_Statistics/2013/index.php/

U.S. Department of Agricultural, National Agricultural Statistics Service. 2015. *2015 Annual Report*. Retrieved from https://www.nass.usda.gov/Publications/Ag_Statistics/2015/index.php/

U.S Department of Agricultural, Risk Management Agency. 2013. *New Annual Forage Pilot Insurance Plan [News Release]*. May 1, 2013. Retrieved from https://www.rma.usda.gov/en/Policy-and-Procedure/Insurance-Plans/Annual-Forage/

______. 2017. *Rainfall and Vegetation Index Insurance Standards Handbook: 2018 and Succeeding Crop Years*. August 25, 2017. Retrieved from https://www.rma.usda.gov/-/media/RMAweb/Handbooks/Coverage-Plans---18000/Rainfall-and-Vegetation-Index---18150/2018-18150--Rainfall-And-Vegetation-Index-Handbook.ashx?la=en/

Wall, M.M., 2004. A close look at the spatial structure implied by the CAR and SAR models. *Journal of Statistical Planning and Inference* 121: 311–324.

Williams, J.R., C.A. Jones, and P.T. Dyke. 1984. A modeling approach to determining the relationship between erosion and soil productivity. *Trans. ASAE* 27: 129-144.

Ziolkowska, J.R. 2018. Profitability of irrigation and value of water in Oklahoma and Texas agriculture. *International Journal of Water Resources Development* 34: 944–960.

CHAPTER III

ESTIMATING THE IMPACTS OF EDA PUBLIC WORKS PROGRAM INVESTMENTS ON COUNTY EMPLOYMENT

Abstract

Evaluating the effectiveness of government programs is an important topic for economic developers. One popular example is the Economic Development Administration’s (EDA) public works program, initially established in 1965. Haughwout (1999) found a significant positive impact of EDA public works projects completed in 1990 on county-level employment over the period 1990 to 1994. We reexamine whether or not this effect continues to hold 20 years later by replicating Haughwout’s specification using data from 2010 to 2014. The results of this study are consistent with those originally reported by Haughwout (1999). We then extend the analysis by incorporating a spatial econometric approach to examine the existence of potential spillover effects. The results indicate that EDA investments not only have a significant positive effect upon the targeted counties’ employment but also have significant positive effects upon neighboring counties’ employment levels. Our findings suggest that public infrastructure investments can be important tools for economic development by positively influencing employment in both the recipient county and neighboring counties.

Keywords: Public works program investments, local economic development policy, spatial fixed effects, spillover effects

Introduction

Researchers have long been interested in whether federal economic development programs play an important role in generating regional economic growth. Evaluations of these government projects have been an important topic for researchers and policymakers seeking to construct successful economic development efforts. One such program that has been evaluated in the past is the EDA's public works program, which has shown positive impacts on local economic growth in the 1980s and 1990s (Kwass et al., 1992; Haughwout, 1999). This paper seeks to find if this relationship still holds, and explores whether it also influences employment in neighboring areas.

The Economic Development Administration (EDA) is a federal agency within the U.S. Department of Commerce created by the Public Works and Economic Development Act (PWEDA) of 1965 (Glasmeier and Wood, 2005). Each year, millions of dollars are allocated for projects that fall into seven categories: Public Works; Economic Adjustment; Research and National Technical Assistance; Local Technical Assistance; Partnership Planning; University Centers; and Trade Adjustment Assistance.[21] The primary focus of this study is on the Public Works Program, whereby one-time matching-funds (typically no more than 50%) are provided towards creating or improving basic infrastructure necessary for business retention/attraction (Watts et al., 2011). The EDA public works program provides matching grants to local communities for activities with the goal such as of the construction of roads, sewers, water supply systems, and industrial parks to promote local industrial growth. Since its beginning in 1965, the EDA has allocated more than half of economic development resources to public works projects (Lake, Leichenko, and Glasmeier, 2004).[22]

[21] Total EDA program outlays have ranged from $238 to $360 million over 2010-2014 based on the EDA annual reports available at www.eda.gov.
[22] Since 2010, the EDA public works program has comprised 55% of EDA funds.

There is a standard argument among economists that place-based development policies are inferior to people-based policy measures, such as worker training and better household mobility (Ravallion and Wodon, 1999; Partridge and Rickman, 2008). EDA projects, however, are generally place-based, and given their continued funding since 1965, it is a useful endeavor to analyze the performance of past projects. Glasmeier and Wood (2005) note that empirical analysis of such regional development programs is sparse. The problem faced by researchers is to separate the signal (the true impact of the program itself) from the noise (confounding impacts such as private investment or other government initiatives). For example, there are many factors that could affect employment generation in urban counties including socioeconomic shifts and activity levels of small and large firms. Similar factors affect rural areas, although likely in different industries. After such factors are considered, EDA public works funding in specific locations may very well contribute to local employment levels – and may even spill over to neighboring areas.

The EDA public works program is designed to improve the economy of communities by expanding and upgrading physical infrastructure to support economic growth. To qualify for EDA grants, a region has to be considered "economically distressed" based upon the unemployment rate and/or lower than average per capita income. Regions must demonstrate the ability to attract matching funds and create a comprehensive plan describing how the developed infrastructure increases economic opportunities or competitiveness for the region (Watts et al., 2011).

Our study attempts to identify the impacts of the EDA public works program on county employment levels using a panel data set on county-level EDA public works expenditures and related variables. The panel nature of our data helps control for omitted variables. A disadvantage of cross-sectional specification is that if variation in the dependent variable is not exogenous, the estimates would be inconsistent. This can be controlled in panel data by exploiting variations over time in geographical units. One of the desirable features of taking a regional approach to development involves the existence of spillovers/externalities, where activities in one place affect people in neighboring places (Pender and Reeder, 2011). Most previous studies appear to have ignored the potential spatial dimension of the economic impacts associated with the EDA public works program. Therefore, we incorporate a spatial econometric approach to our analysis, and assess whether EDA investments have spillover effects in nearby counties. As a robustness check on our initial and spatial specifications, we estimate the causal effect of the EDA public works program on county employment growth using a propensity score matching method.

The hypotheses to be tested are:

1. EDA public works spending has a positive impact on local employment.
2. There are positive spatial spillover effects from EDA public works investments on neighboring counties employment.

Literature Review

Several studies have attempted to measure the impacts of EDA projects on local economies. Pender and Reeder (2011) provide a tabulated summary of such studies. Most of these studies found some evidence of positive employment impacts of EDA public works investments (Barrows and Bromley, 1975; Kwass et al., 1992; Burchell et al., 1997; Burchell et al., 1998; Haughwout, 1999; Arena et al., 2008). For example, Barrows and Bromley (1975) found evidence of increased employment resulting from EDA spending, with lager impacts in rural counties, where public works projects occurred. Burchell et al. (1998) estimated the direct and multiplier effects of EDA public works investments on total employment using county-level data from 1990 to 1994. They estimated that nine jobs were created per $10,000 of EDA spending. Haughwout (1999) found similar effects of EDA spending as Burchell et al. (1998) across several econometric specifications considered, but these were substantially smaller in magnitude.

Evidence of the impacts of EDA public works investments on total income growth remains less conclusive (Martin and Graham, 1980; Haughwout, 1999). For example, Martin and Graham (1980) found that EDA-assisted counties experienced significant improvements in relative personal income growth rates during the period of aid receipt. The income growth rates varied with respect to both the receipt of and the relative amount of aid. However, they did not find positive impacts upon income in the post-aid period. Haughwout (1999) also found no significant effect of EDA spending on income at the county level.

Glasmeier and Wood (2005) analyzed temporal and spatial patterns in the allocation of EDA projects between 1965 and 1997. The largest recipients of EDA funds were major urban cities such as Los Angeles, CA, Washington D.C., and New York. Glasmeier and Wood (2005) noticed that the emphasis of EDA programs has varied over time in terms of rural and urban spending. In the 1970s, urban spending was preferred in view of the urban unrest of the time. In the 1980s, the collapse of the agricultural and natural-resources-based economy caused the EDA to emphasize more spending on rural counties. By the 1990s, an urban bias returned and is attributed to the shutdown of major urban military bases and natural disasters in the electorally powerful state of Florida. Glasmeier and Wood (2005) also noted that, for most of its existence, EDA did not fund larger projects over extended periods of time, a typical U.S. county did not receive any funding from the EDA, and the majority of counties that received EDA funding did so for only one activity. Arena et al. (2008) found significant positive employment impacts resulting from all EDA spending in rural counties, but insignificant impacts in urban counties from 1990 to 2005. They also estimated impacts of different types of EDA projects. The smallest cost per job created was found for business incubator projects, while the largest cost per job created was found for community infrastructure projects.

Haughwout (1999) assessed the impact of EDA public works investments during 1990 on county labor markets for the period 1990 to 1994. He examined the relationships between EDA public works investments and several county-level outcomes: private nonfarm and farm employment, cost per job created, and average compensation per employee. He found EDA spending had a significant positive impact on private nonfarm employment, and that the mean cost per job created was $9,325. He also found no significant impacts of EDA spending on compensation per employee and on farm employment. In this study, we initially follow the analysis conducted by Haughwout (1999), using data from 2010 to 2014, to determine whether the impacts of EDA public works investments remain consistent 20 years later. We then extend the analysis to measure any spatial spillover effects from EDA public works investments at the county level. A reasonable assumption would be that personnel necessary to complete the projects receiving funding may be located in areas neighboring the county receiving funds. If these are neglected, the estimated effects of EDA investments are more likely to be biased due to omitted relevant variables. Therefore, controlling for the existence of any spatial spillover effects from EDA spending would lead to better policymaking decisions for allocating these limited economic development resources.

Econometric analyses that use geographically aggregated data (as opposed to county-level data) tend to find a lower impact of public expenditures on response variables, such as output elasticity, or productivity. The existence of spatial spillovers from public expenditure is thought to be the underlying reason for this (Aschauer, 1989; Munnell, 1990; Alvarez, Arias, and Orea, 2006). Spatial spillovers can be caused by public infrastructure designed to increase the connectivity, or linkage, of a region to enable participation in economic activity; examples include interstate highways, railways, internet, or bridges. Therefore, the impacts of public expenditure at one location cannot be adequately measured at the local level alone, but should consider impacts upon neighboring locations as well. Spatial spillover effects have been explored in other areas of economics. For example, countries that grow fast are found to be clustered together (Moreno and Trehan, 1997; Alvarez, Arias, and Orea, 2006). Holtz-Eakin and Schwartz

(1995) estimated a state-level production function for private output productivity. Their econometric specification measured spillovers by defining an effective public infrastructure capital as a function of within-state infrastructure as well as cross-state infrastructure. Their results did not support the notion of spillover among states in terms of the productivity impact of public capital. Tong et al., (2013) used a spatial Durbin model to estimate the impact of state transportation infrastructure on agricultural output. Their results with respect to the spillover effects of transportation were sensitive to the specification of the spatial weight matrix. In terms of agricultural output, they found that investment on transportation infrastructure would produce larger spatial spillovers in the central U.S. than in the coastal or border areas. Such spatial spillovers have not been rigorously tested in the case of EDA public works expenditures.

Econometric Procedure

State and Year Fixed Effects

In order to examine the effects of EDA public works grants on county employment levels, we start with Haughwout's (1999) specification[23] as follows:

$$ln(Y_{it}) = \tau_t + \xi_{is} + \gamma ln\left(EDA_{i(2010)}\right) + X_{it}\beta + \alpha ln\left(EMP_{i(2008)}\right) + \varepsilon_{it}, \quad (19)$$

where Y_{it} represents total employment in county i during year t, τ_t and ξ_{is} represent vectors of year and state fixed effects dummies, respectively, $EDA_{i(2010)}$ is the total value of EDA funding for projects awarded during the fiscal year 2010[24], and X_{it} denotes a vector of economic and demographic factors believed to determine local employment. $EMP_{i(2008)}$ is total employment in county i in 2008 controlling for the unmeasured county-level fixed effects. α, β, and γ are parameters to be estimated, and ε_{it} are independently and identically distributed error terms with

[23] In this specification, we are focusing on the effect of EDA funding in a single year 2010 on county employment levels over the next several years (2010-2014).

[24] We take the natural logarithm of EDA funding to define $ln(0) \approx 0$ because EDA provided public works grants to only about 108 counties in 2010.

zero mean and constant variance σ^2. Equation (1) is estimated using ordinary least squares (OLS) with the state and year fixed effects.[25]

We are mostly interested in the direct impact of EDA investments on county employment (i.e., γ), but we modify our specification to allow for spillover effects as laid out below.

Spatial Interaction and Spillover Effects

It is possible that EDA funds provided to a county might influence employment in neighboring areas. This could be due to employees who cross county lines to work, or from businesses in nearby communities boosting employment in response to increased spending. To evaluate whether the EDA public works funding generates interregional economic activity, we measure the spatial spillover effects of EDA investments on the level of county employment. Thus, we extend Haughwout's (1999) specification to a spatial econometric model by including spatial interaction effects.

Before estimating a spatial econometric model, we preliminarily test for the existence of spatial dependence using panel versions of both the standard Lagrange Multiplier (LM)-tests and the locally robust LM-tests.[26] Then, following Elhorst (2017), three different types of spatial interaction effects are considered in this study. First, along the lines of a traditional spatial lag model, an endogenous interaction effect is included to measure whether total employment in county i depends on neighboring counties' employment levels. Second, an exogenous interaction effect is considered to determine the effects of contiguous counties' EDA public works grants received on total employment in county i. This model, on its own, would be a spatial lag of X framework (Vega and Elhosts, 2015). Finally, an interaction effect among the error terms is

[25] In particular, a least-squares dummy variables (LSDV) estimator is used in order to estimate the state and year fixed effects.

[26] Both the tests are implemented based on a pooling assumption, not allowing for any kind of individual effects by employing a within transformation (time-demeaned) (Anselin et al., 1996 and Elhorst, 2014a).

included to account for whether county i's unobserved factors are correlated with those of neighboring counties – the traditional spatial error approach.

Including all possible spatial interaction effects, our general nesting spatial model can be specified as:

$$(20)\qquad ln(Y_{it}) = \rho\sum_{j=1}^{N} w_{ij} ln(Y_{jt}) + \gamma EDA_{i(2010)} + X_{it}\beta + \theta\sum_{j=1}^{N} w_{ij} EDA_{j(2010)} + \alpha_i + u_{it}$$

$$u_{it} = \lambda\sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it}$$

where the spatial weight matrix w_{ij} is a $N \times N$ matrix describing the spatial dependence between counties and is created from queen contiguity weights. The variables $\sum_{j=1}^{N} w_{ij} Y_{jt}$, $\sum_{j=1}^{N} w_{ij} EDA_{i(2010)}$, and $\sum_{j=1}^{N} w_{ij} u_{jt}$ denote the spatially weighted average values of county employment levels, EDA public works grants awarded in counties *j* during the fiscal year 2010, and the error terms from neighboring counties j at year t, and the corresponding parameters ρ, θ, and λ measure the strength of spatial dependence between neighboring counties. α_i represents either county fixed effects or random effects controlling for spatial heterogeneity of counties' employment levels. In the fixed effects model, a dummy variable is used for each county, while in the random effects model, α_i is used as a random variable that is independently and identically distributed with zero mean and constant variance σ_α^2 and is not correlated with u_{it}. Note that the explanatory variable $EMP_{i(2008)}$ (i.e., the level of county employment in 2008) in equation (1) is excluded from equation (2), but either county-specific fixed effects or random effects are included.[27] To estimate the spatial fixed or random effects for panel data, equation (2) is estimated using a Maximum likelihood (ML) estimator.[28]

However, the general nesting spatial model with all possible spatial interaction effects is rarely done in empirical studies for two reasons: the parameter identification problem and the problem of overfitting (Elhorst, 2014b). Moreover, numerous studies apply spatial panel data models while controlling for spatial and/or time fixed or random effects (Baltagi and Li, 2004; Elhorst, 2005). Elhorst (2014c) demonstrated that a spatial model specification with either fixed effects or random effects outperforms its counterparts without those effects. Therefore, we specify three simpler models considering one or two types of spatial interaction effects controlling for either the county-specific fixed effects or random effects. These are: (1) the spatial lag random effects model considering the endogenous spatial interaction effect WY_t, (2) the spatial error fixed effects model considering the spatial interaction effect among the error terms Wu_t, and (3) the spatial Durbin error fixed effects model considering both the exogenous interaction effects $WEDA_{2010}$, and Wu_t.

The Hausman test is used to determine whether the spatial fixed effects or random effects model is more appropriate to describe the relationship between EDA public works investments and county employment. It tests whether random effects can replace fixed effects, when the spatial fixed effects appear to be significant, and follows a chi-squared distribution with possible 2*K*+1 degrees of freedom (Elhorst, 2014b). An advantage of the spatial fixed effects specification is that unmeasured individual heterogeneity in each spatial unit can be captured through the use of county dummy variables and these fixed effects can be correlated with the other explanatory variables. The benefit of the spatial Durbin error model ($\rho = 0, \theta \neq 0$) over the spatial lag model ($\rho \neq 0$) is that the spatial spillover effects can be directly captured in this specification.

[27] Haughwout's (1999) suggested that either approach could be used to control for additional determinant of county-level employment.
[28] We used the packages "splm" (Millo and Piras, 2012) available in the R programming language.

Average Treatment Effects

As a robustness check on our initial (and spatial) specifications, we estimate average treatment effects of obtaining EDA funding. A matching method is used to estimate the causal effects of EDA funding for projects on local employment growth (Rubin, 1977; Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002; Imbens, 2004). We measure the average treatment effect (ATE) as the causal differences of both the employment level and the employment growth rate between the treated counties, (those that received EDA grants), and the control counties, (those that did not receive EDA funding). Thus, the ATE for the treated counties can be written as follows:

$$ATE = E(Y_{i1}|T_i = 1) - E(Y_{i0}|T_i = 1), \tag{3}$$

where Y_{i1} and Y_{i0} are outcomes of interest when county i received EDA grants (1) and when county i did not receive EDA funding (0), respectively. $T_i = 1$ $(= 0)$ if county i was assigned treatment (control). The problem is that we can estimate $E(Y_{i1}|T_i = 1)$, but not $E(Y_{i0}|T_i = 1)$ because we can only observe the average economic growth of the recipient counties $E(Y_{i1}|T_i = 1)$ and non-recipient counties $E(Y_{i0}|T_i = 0)$. The counterfactual terms $E(Y_{i1}|T_i = 0)$ and $E(Y_{i0}|T_i = 1)$ are not observed. In particular, $E(Y_{i1}|T_i = 0)$ is the expected value of economic growth of the recipient counties had they not received EDA funding, while $E(Y_{i0}|T_i = 1)$ is the expected value of economic growth of non-recipient recipient counties had they received EDA grants.

To substitute for the unobservable control counties, we estimate a hypothetical counterfactual using a set of comparison counties that have similar pretreatment economic and demographic characteristics as the treated counties (Dehejia and Wahba, 2002). We first estimate a logit model on whether a county is treated (i.e., receives EDA funding), using socioeconomic variables X_i that may affect the likelihood of being awarded a grant. The propensity score is the conditional probability of receiving EDA grants given the pretreatment socioeconomic characteristics (Rosenbaum and Rubin, 1983) defined as follows:

(4) $$p(X_i) \equiv \Pr(T_i = 1|X_i) = E(T_i|X_i).$$

The resulting propensity score is then used to match each treatment county i ($T_i = 1$) to a set of comparison counties ($T_i = 0$) with a similar propensity score. That is, each treated county can be matched to a control county that had a similar likelihood of receiving EDA funding – but was not awarded a grant. We test whether the treated and control counties have the same distribution of socioeconomic characteristics X_i, using a test developed by Becker and Ichino (2002). Although there are several matching methods available in the literature, we use both the nearest neighbor and kernel methods to select a set of comparison counties based on the closeness of the propensity score to the treatment county (Becker and Ichino, 2002 and Dehejia and Wahba, 2002). The nearest neighbor method selects 5 neighbors of comparison counties whose propensity scores are closest to the treated county, while kernel matching uses all of the comparison counties from the control group by inversely weighting their distance from the treated county. After the treatment and control counties are constructed, the ATE of the EDA public works program is estimated as the average difference in employment level (and employment growth) between the treatment and control counties as specified by equation (3).

Data

The data on EDA public works investments during the fiscal year 2010 were obtained from the annual reports[29] of the U.S. Department of Commerce's Economic Development Administration. The data on county-level economic and demographic measures, including county-level private, non-farm employment series, come from the U.S. Census Bureau's annual data series for the years 2010 to 2014. Data from only the Continental United States were used, all data from the

[29] The EDA annual reports for fiscal years 2007-2017 are available at www.eda.gov.

states of Alaska and Hawaii were excluded. In addition, data from three counties within the Continental United States (Broomfield County, Colorado; Shannon County, South Dakota; and Bedford City, Virginia) were excluded due to missing data and/or inconsistency with spatial data used for spatial analysis. The three counties excluded did not receive EDA funding nor were adjacent to counties receiving EDA funding, and thus should not influence the analysis. Figure 1 illustrates the spatial distribution of urban/rural counties that received EDA public works grants during the fiscal year of 2010.

It is important to note that we follow Haughwout's (1999) specification in choosing these variables. County-level private, non-farm employment is used to measure local employment growth. For the explanatory variables, the percentages of small and big firms are included to determine whether the size distribution of firms influences county employment opportunities. Median house values, measured in 2010 dollars, are also included as a proxy of land value. The urban/rural status of each county is included to control for different employment opportunities and growth rates between metropolitan and non-metropolitan areas. Demographic factors include the racial and ethnic composition of the population potentially associated with county employment. The level of county employment in 2008 is included to control for the unobserved county-level fixed effects that are likely to influence county employment growth.[30] In each year, 3,106 counties are included for the fixed effects analysis with and without spatial interaction effects. A total of 15,530 observations are used for the years 2010 to 2014. Variable descriptions and summary statistics are presented in Table 1. The average EDA award among recipient counties is $49,449, which is skewed by the high number of counties receiving $0. The average of private, non-farm employment across U.S. counties over 5 years is 36,211 jobs with a high standard deviation.

[30] Haughwout (1999) controlled for unmeasured county-level fixed effects by including the county employment level in 1988 that is likely to affect the level of county employment and may be correlated with receiving EDA funding.

Data for the average treatment effects methodology is focused on the 3,106 counties only during the fiscal year of 2010 (i.e., estimating the likelihood of receiving funding in 2010). The unemployment rate is included in this analysis because the EDA specifies that counties with relatively high unemployment rates are qualified for EDA assistance. Variable descriptions and summary statistics across metropolitan and non-metropolitan areas for this ATE methodology are presented in Table 2. An average of $78,911 in EDA funding was provided to urban counties compared to an average of $31,911 to rural areas in 2010. For 2010, the mean employment level in metropolitan counties is 83,200 and is 6,370 in rural counties.

Results

Table 3 presents the results of the models: the OLS with state and year fixed effects, the spatial lag random effects, the spatial error fixed effects, and the spatial Durbin error fixed effects, respectively. In all model specifications, the natural logarithm of private, non-farm county employment for the period 2010 to 2014 is used as the dependent variable. In the OLS model specification, the natural log level of county employment in 2008 is included to control for unobserved variations in county employment as described in Haughwout (1999). For the spatial model specifications, either the county-specific fixed or random effects is included to control for unobserved spatial heterogeneity in county employment[31], as well as the same economic and demographic factors used for the OLS model following Haughwout's (1999) specification. In particular, the percentages of small/big firms, the urban status of the county, the percentages of both African American and Hispanic populations in 2010, and the natural log of median house value in 2010 are used to control for other socioeconomic characteristics expected to influence the level of county employment. The percent Hispanic population is an additional variable that was not included by Haughwout (1999).

[31] Note that Haughwout (1999) suggests using county fixed effects as an alternative to including base-year employment in the specification.

State and Year Fixed Effects Results

The first column of Table 3 presents the results of the OLS model. The value of the adjusted R^2 is greater than 0.99. The estimated effects and their significance are very similar to Haughwout's (1999) estimates.[32] The only exception is the estimated effect of the percentage of black population, which was not significant in Haughwout's (1999) analysis but is significant in this study. Most importantly, the amount of EDA investments in the county has a significant positive effect on the level of county employment at the 10% level. This implies that a 1% increase in EDA spending results in county employment levels that are approximately 0.00088% higher. This is remarkably similar to the estimate reported by Haughwout (1999) using data from the period 1990 to 1994. Haughwout (1999) argues that his results show that EDA funding has impacts for at least 4 years; the updated results confirm this assessment. The similarity of these results supports that the positive impact of EDA public works investments on the level of employment in U.S. counties is consistent 20 years later.

The percentages of small/big firms are significantly associated with county employment levels, but in opposite directions. As the proportion of small firms increases, the level of county employment decreases, while the opposite is observed for the proportion of big firms, indicating that the size distribution of firms plays a significant role in local economic growth. For instance, an economy characterized by a high proportion of big firms is advantageous for increasing county non-farm private employment. The estimated coefficient on the urban status of the county is positive and significant at the 1% level, suggesting that there is a benefit associated with being located in a metropolitan county. The percentages of black and Hispanic populations in 2010 are found to be significantly associated with county employment levels, but in opposite directions. This indicates that counties with a high proportion of black residents have lower levels of

[32] A comparison of the exact specification results from Haughwort's (1999) with those for 2010-2014 are presented in Appendix Table 6.

employment, while the opposite relationship is observed for counties with a high proportion of Hispanic residents. As the median 2010 house value increases, the level of county employment increases, suggesting that counties with higher housing values have an advantage for employment growth. The level of county employment in 2008 has a strong and positive influence on county employment levels, 0.962, indicating that prior county employment is an important determinant of future levels. While the ongoing recession at that time may influence the results, it is worth noting that the estimate is strikingly similar to Haughwout's (1999) estimate of 0.964. The estimated state and year fixed effects, included in Appendix Table 7, are all significant with the exception of the year 2011.

Spatial Interaction and Spillover Effects Results

Before considering the estimates of the spatial interaction and spillover effects models, we first attempt to test and control for the potential spatial dependence on the level of county employment. We used panel versions of both the standard LM-tests and the locally robust LM-tests. For spatial lag dependence, the results of both tests suggest that there is no significant spatial interaction effect between neighboring counties, with the standard LM test and locally robust LM test statistics of 0.223 and 0.024 and corresponding *p*-values of 0.637 and 0.877, respectively. For spatial error dependence, the standard LM test and locally robust LM test statistics are 5.651 and 5.453 and their corresponding *p*-values are 0.017 and 0.020, respectively, indicating a significant spatial correlation between neighboring counties at the 5% level.

We now turn to the estimation results of the spatial models. With one exception, the results of all three spatial model estimates are similar in direction and significance to those found in the OLS model. Strikingly, the single difference of the spatial models from the OLS model is the estimate found for the percentage of black population. The estimate for the OLS model is negative and relatively small while in all three spatial models the estimates are positive and much greater in magnitude.

The results for the spatial lag random effects model are presented in the second column of Table 3. In this model, the county-specific effects are treated as random to exploit the cross-county information. Interestingly, the estimated coefficient upon the county receiving EDA investments is 0.054 and statistically significant at the 1% level. One limitation of this model specification is that we can only obtain the direct (global) effects. The estimate of spatial lag effect (ρ) is also insignificant, indicating that there is no association between neighboring counties' employment levels, consistent with what was obtained from the standard and robust LM tests. The coefficient on the county random effect (φ) (i.e., a variance component) is statistically significant at the 1% level, indicating the existence of unobserved county-specific heterogeneity in county employment levels.

The third column of Table 3 presents the estimation results for the spatial error fixed effects model. The model estimated the level of county non-farm private employment, while controlling for the county-specific effects as fixed by ignoring information in cross-county variation. The estimated coefficient on receiving EDA funding is 0.026 and statistically significant at the 1% level substantially increased in magnitude from Haughwout's (1999) and our OLS estimates. This supports a significant role for EDA investments in generating jobs in the county. The estimate of spatial error parameter (λ) (approximately 0.327) is statistically significant and positive, indicating that unobserved characteristics are correlated among neighboring counties.

After considering the estimates of the spatial error fixed effects model, we test whether the spatial fixed effects significantly differ from random effects using the Hausman test. The value of the Hausman test is 390.75 with a *p*-value less than 0.01. The degree of freedom is 7, and the critical value at 1% level for the χ^2 distribution (with 7 degrees of freedom) is 18.48. Hence, we can clearly reject the spatial error random effects model in favor of the spatial error fixed effects model.

Finally, in order to estimate the spatial spillover effect from EDA investments in neighboring counties onto a county's employment, the spatial error fixed effects model is extended to the spatial Durbin error fixed effects model incorporating the exogenous spatial interaction effect. The estimation results are reported in the last column of Table 3. The coefficient on the county receiving EDA investments is identical to the estimate found in the spatial error fixed effects model, 0.026, and is significant at the 1% level. As hypothesized, a significant positive spillover effect of neighboring counties receiving EDA investments is found at the 1% level, which demonstrates evidence of beneficial spillovers. Specifically, a 1% increase in the average EDA investments provided to contiguous counties increases the level of county employment by approximately 0.037%. This indicates that spillovers from EDA public work investments received by neighboring counties raises the level of county employment. That is, EDA investments in a neighboring county can significantly influence own-county employment – in particular, for cases where multiple neighboring counties are awarded. This is similar to what has been described for other public infrastructure investments (Cohen and Morrison, 2004). The estimated effects of the other variables reported, including the spatial error effect, are consistent with those of the spatial error fixed effects model in terms of their signs and significance. The magnitude of the estimated effects of this model decreased slightly when compared with the parameter estimates of the spatial error fixed effects model with one exception; the estimate of the proportion of big firms increased slightly. These estimates are likely to be biased (upward/downward) as a result of omitting a relevant variable if the spatial spillover effects are not included.

Average Treatment Effects Results

We estimate the effect of EDA public works program on both the employment level and the employment growth rate for U.S. counties. First, we estimate the probability of receiving EDA funding using a logit model. The percentages of both small and big firms, race and ethnicity of the population, median house values (natural logarithm), and county unemployment rate are used to estimate propensity scores. The estimation results are presented in Table 4. As expected, a high unemployment rate increases the probability of receiving EDA grants, confirming that economically distressed counties are more likely to qualify for EDA funds.[33] As the percentage of small firms increases, the probability of receiving EDA investments decreases, while the opposite is observed for the percentage of big firms. Interestingly, recipient counties of EDA funding are more likely to have high median house values rather than low median house values.

The value of the pseudo R^2 for the logit model is 0.051, which is similar to what other studies have found using a propensity score matching method to estimate the probability of receiving public funds. For example, Pradhan and Rawlings (2002) found a pseudo R^2 of 0.052 for the probability of obtaining social investment fund for an education project. Carboni (2011) found a pseudo R^2 of 0.048 for the probability of a firm of being awarded public R&D grants.

We test the assumption of common support for the propensity score estimator in terms of the distribution of covariates between treated and control counties (Becker and Ichino, 2002), as illustrated in Figure 2. Most propensity scores in both treatment and comparison counties fell into the range of [0.01, 0.35]. This allows us to estimate the average treatment effects of EDA public works program.

[33] Additionally, we used the median household income to measure whether per capita income has an impact on the probability of awarding EDA funds. We found no significant impact. Therefore, per capita income was excluded in the final model.

We compare the results of both the nearest neighbor and kernel matching methods to check the robustness of the estimation of the ATE for the EDA public works investments as presented in Table 5. We find that the estimates of the ATE are positive and statistically significant at the 1% or 5% level, suggesting that EDA public works spending increases the level of employment by approximately 1.11 to 2.66 jobs[34] (nearest neighbor versus kernel matching) in economically disadvantaged counties. The effectiveness of EDA public works investments differs by geographic locations. The EDA investments increase the employment level by approximately 1.44 to 2.58 jobs in urban counties, nearest neighbor versus kernel matching respectively. For rural county employment levels, only the kernel matching method identifies a 1.60 unit increase in job generation. When 2014 employment data are used, the estimated coefficients of the ATE for EDA public works spending are similar to the results for the level of employment in 2010, indicating that the impacts of the EDA public works program last at least 4 years. These results are consistent with the results obtained in both Haughwout's (1999) and our OLS models examining the impact of EDA funds upon the level of employment. However, when compared over time, neither matching method indicated that the EDA investments have significant impact on county employment growth rates as reported in Table 5. This shows that, in comparison to otherwise similar counties, those counties that received EDA funds have higher employment for at least 4 years, but did not have increased growth rates in employment over time (from 2010-2011, 2010-2012, etc.). This implies that EDA investments are beneficial for generating employment in economically distressed counties during the period of funding receipt, but do not have a significant effect upon employment growth rate in the immediate following years. This result is consistent with Martin and Graham's (1980) lack of results when they explored the impact of EDA assistance on county income growth.

[34] In order to convert the natural log of employment to actual numbers of jobs created, we take an exponential of that value (i.e., PNFEMP = $e^{ln(\text{PNFEMP})} = e^{0.405} = 1.11$ jobs).

Conclusions

The EDA's public works program has been the topic of several empirical studies from the 1970s to 2000s, with most results suggesting positive impacts for local economies. In particular, Haughwout (1999) found that EDA public works investments have significant positive effects on county employment levels. We first reexamine whether these effects continue to hold 20 years later by replicating the Haughwout's (1999) model specification using data from 2010 to 2014. The results of our analysis are consistent with those originally reported by Haughwout (1999), suggesting that the EDA public works program remains an effective tool for regional economic development.

We extend this analysis by incorporating an econometric approach that accounts for the possible spillover effects of EDA public works investments. Such spillovers could occur if businesses in neighboring counties are influenced by EDA expenditures. The results from the spatial Durbin error fixed effects model indicate that there are significant positive spillover effects among neighboring counties receiving EDA public works investments, supporting the idea that infrastructure investments impact the economies of surrounding locations as well as those directly receiving the funds. These impacts to neighboring counties were typically not assessed in previous studies, and the results here show that they are an important component of such policy efforts.

We check the robustness of the results using a propensity score matching method. The average treatment effect of EDA funding for projects is positive and statistically significant, suggesting that EDA public works spending increases the level of county employment. The results found that the average treatment effects of EDA public works investments differs by rural/urban status, with larger impacts in urban locations. This is consistent with Haughwout's original analysis (1990-1994) and our OLS analysis (2010-2014). The EDA public works investments had a significant impact on employment levels over the 4 year period. In regards to county employment growth rate, EDA investments do not seem to have a significant impact over the period of 2010-2014. This suggests that EDA investments are beneficial for generating jobs during the period of funding receipt and lasting at least 4 years after funding receipt, but do not have significant impacts upon employment growth rate in the post aid period.

This study has important policy implications for the EDA public works program, which has a long history in U.S. economic development. The results show that EDA public works investments not only have a significant economic effect upon the targeted counties employment but they also have significant positive effects upon neighboring counties' employment growth. Our findings suggest that the EDA public works program is effective at helping increase employment in economically distressed target counties, as well as nearby counties. However, the program does not necessarily lead to continued employment growth over longer periods of time post receipt of the aid – and thus should be viewed as only a short-term shock that does not influence future conditions for employment growth.

Table 3-1 Descriptive Statistics

Variable	Description	Mean	Std. dev.	Source
EDA	EDA grant amount awarded; projects funded in 2010 ($2010)	49,449.13	305,855.14	(1)
PNFEMP	Total private, non-farm employment	36,211.98	133,101.43	(2)
SMSHARE	% of firms with less than 10 employees	76.76	5.73	(2)
BGSHARE	% of firms with more than 1,000 employees	0.04	0.10	(2)
URBAN	Dummy=1 if a component county located in metropolitan area	0.37	0.48	(2)
BLACK	% Black population, 2010	8.97	14.56	(3)
HISP	% Hispanic population, 2010	8.33	13.26	(3)
MHV	Median house value, 2010 ($2010)	131,381.78	85,943.14	(3)

Note: (1) U.S. Department of Commerce, (2) U.S. Census Bureau 2010-2014, and (3) U.S. Census Bureau 2010.

Table 3-2 Descriptive Statistics for EDA Investment and County Employment by Urban/Rural Status, 2010

		Urban Areas		Rural Areas	
Variable	Description	Mean	Std. Dev.	Mean	Std. dev.
EDA	EDA grant amount received; projects funded in the year 2010 ($)	78,911.13	416,199.84	31,911.15	212,976.10
PNFEMP	Total private, non-farm employment	83,200.69	199,556.77	6,370.34	7,074.46
SMSHARE	% of firms with less than 10 employees	74.90	5.15	78.20	5.46
BGSHARE	% of firms with more than 1,000 employees	0.06	0.08	0.03	0.09
BLACK	% Black population	10.97	13.59	7.78	14.98
HISP	% Hispanic population	8.95	12.19	7.96	13.84
MHV	Median house value ($)	174,632.79	102,649.66	105,635.54	61,137.49
UNEMP	Unemployment rate	9.35	2.54	9.37	3.47

Table 3-3 Estimation Results for the OLS and Spatial Models: EDA Public Works Investments and County Employment

Dependent Variable		**Spatial Effects Models**		
lnPNFEMP	**OLS Fixed Effects Model**	**Spatial Lag Random Effects Model**	**Spatial Error Fixed Effects Model**	**Spatial Durbin Error Fixed Effects Model**
Constant		-8.519^{***}		
		(0.569)		
SMSHARE	-0.008^{***}	-0.017^{***}	-0.152^{***}	-0.152^{***}
	(0.000)	(0.001)	(0.001)	(0.001)
BGSHARE	0.252^{***}	0.570^{***}	1.517^{***}	1.528^{***}
	(0.014)	(0.019)	(0.074)	(0.074)
URBAN	0.025^{***}	1.032^{***}	0.539^{***}	0.537^{***}
	(0.003)	(0.051)	(0.018)	(0.018)
BLACK2010	-0.001^{***}	0.013^{***}	0.006^{***}	0.006^{***}
	(0.000)	(0.002)	(0.001)	(0.001)
HISP2010	0.001^{***}	0.008^{***}	0.002^{***}	0.001^{**}
	(0.000)	(0.002)	(0.001)	(0.001)
lnMHV2010	0.051^{***}	1.530^{***}	1.611^{***}	1.606^{***}
	(0.005)	(0.049)	(0.018)	(0.018)
lnPNFEMP2008	0.962^{***}	—	—	—
	(0.002)	—	—	—
lnEDA2010	0.0009^{*}	0.054^{***}	0.026^{***}	0.026^{***}
	(0.001)	(0.008)	(0.003)	(0.003)
WlnEDA2010				0.037^{***}
				(0.006)
$\boldsymbol{\rho}$		0.024		
		(0.021)		
$\boldsymbol{\lambda}$			0.327^{***}	0.325^{***}
			(0.012)	(0.012)
$\boldsymbol{\varphi}$		149.196^{***}		
		(4.290)		
County effects		Random	Fixed	Fixed
N	15,530	15,530	15,530	15,530
Adj. R^2	0.9997			

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level. Standard errors are shown in parenthesis

Table 3-4 Logistic Regression Results for EDA Public Works Funding, 2010

Independent Variable	Coefficient	Std. dev.
% of firms with less than 10 employees	-0.084***	0.020
% of firms with more than 1,000 employees	1.726**	0.741
% Black population	0.000	0.007
% Hispanic population	0.009	0.006
Log(Median House Value)	0.457**	0.190
Unemployment Rate	0.089***	0.032
Constant	-3.365	2.697
Log Likelihood	-445.069	
Pseudo R-Squared	0.051	

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level.

Table 3-5 Average Treatment Effects of EDA Public Works Program

	Nearest Neighbor		Kernel Matching	
Dependent Variable	Difference	T-stat	Difference	T-stat
lnPNFEMP2010	0.405**	2.17	0.978***	5.68
lnPNFEMP2010_Urban	0.526**	2.45	0.951***	4.79
lnPNFEMP2010_Rural	0.278	1.60	0.588***	3.74
lnPNFEMP2014	0.425**	2.26	0.995***	5.72
lnPNFEMP2014_Urban	0.527**	2.42	0.959***	4.76
lnPNFEMP2014_Rural	0.312*	1.78	0.608***	3.82
%Δ PNFEMP 2010-2011	0.007	1.18	0.002	0.25
%Δ PNFEMP 2010-2012	0.015	1.65	0.002	0.23
%Δ PNFEMP 2010-2013	0.016	1.08	0.010	0.82
%Δ PNFEMP 2010-2014	0.019	1.15	0.008	0.56

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level.

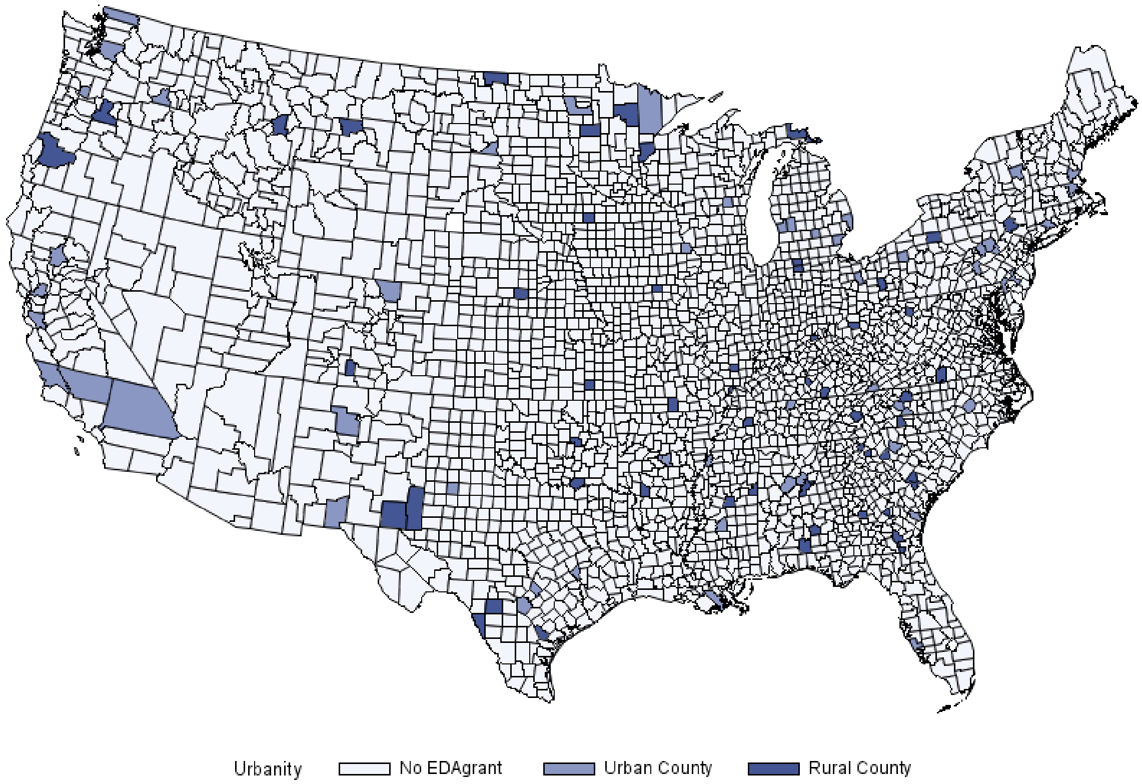


Figure 3-1 Spatial distribution of urban/rural counties receiving EDA grants, 2010

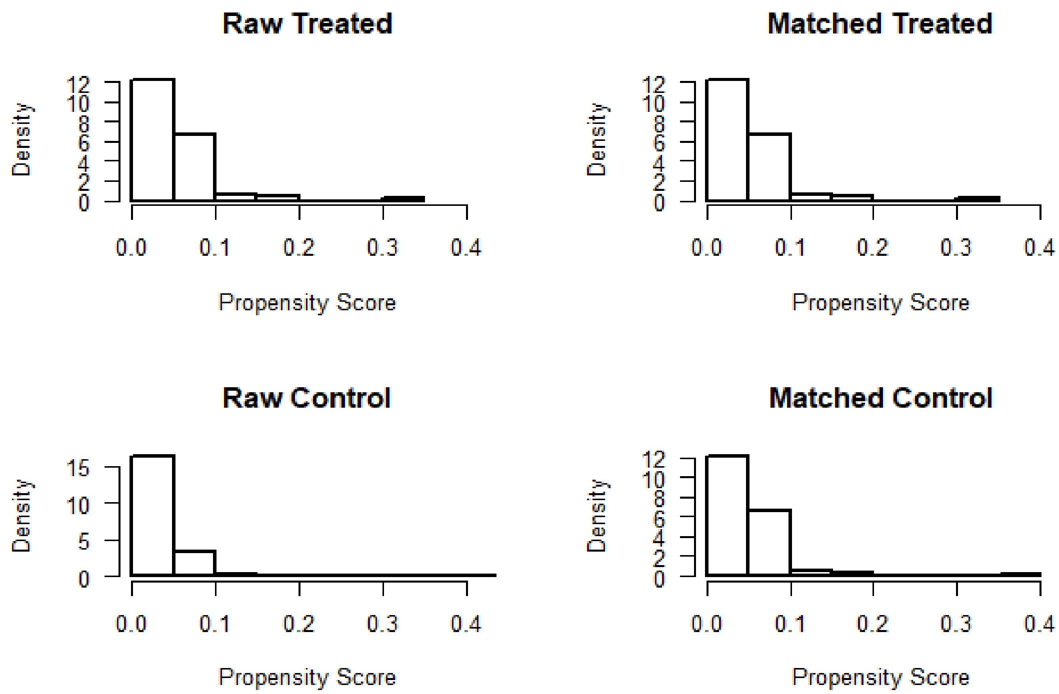


Figure 3-2 Distributions of the estimated propensity scores

REFERENCES

Alvarez, A., C. Arias, and L. Orea. 2006. Econometric testing of spatial productivity spillovers from public capital. *Hacienda Pública Española / Revista de Economía Pública,* 178-(3/2006): 9-21.

Anselin, L., A.K. Bera, R. Florax, and M.J. Yoon. 1996. Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics* 26(1): 77-104

Arena, P., J.A. Adams, K. Noyes, S. Rhody, and M. Noonan. 2008. Construction grants program impact assessment report: Volume 1 report on investigation and results (Grant Thornton research report with ASR Analytics). Retrieved from http://www.eda.gov/ PDF/EDAConsImpactStudyVolume1FINAL.pdf

Aschauer, D.A. 1989. "Is Public Expenditure Productive?" *Journal of Monetary Economics* 23 (2): 177-200.

Baltagi, B.H., and D. Li. 2004. Prediction in the panel data model with spatial autocorrelation. In: Anselin, L., R. Florax, and S.J. Rey. (eds) Advances in spatial econometrics: methodology, tools, and applications. Springer, Berlin, p 283-295.

Barrows, R.L., and D.W. Bromley. 1975. Employment impacts of the Economic Development Administration's public works programs. *American Journal of Agricultural Economics* 75: 46-54.

Becker, S.O., and A. Ichino. 2002. Estimation of Average Treatment Effects Based on Propensity Scores. *The Stata Journal* 2: 358-377.

Burchell, R.W., L.J. Pignataro, F.H. Griffis, J. Epling, A.F. Haughwout, D. Varady, J. Looye, et al. 1997. Public works program: Performance evaluation (NTIS No. PB97– 175434/A15). New Brunswick, NJ: Rutgers University.

Burchell, R., A. Haughwout, M. Robison, N. Shad, and W. Dolphin. 1998. Public Works Programs–Multiplier and Employment-Generating Effects, prepared for U.S. Department of Commerce, Economic Development Administration Office of Program Research and Evaluation (EDA Project No. 99-06-07415).

Carboni, O.A. 2011. R&D subsidies and private R&D expenditures: Evidence from Italian manufacturing data. *International Review of Applied Economics* 25: 419-439.

Cohen, J.P., and C.J. Morrison. 2004. Public Infrastructure Investment, Interstate Spatial Spillovers, and Manufacturing Costs. *The Review of Economics and Statistics* 86(2): 551-560.

Dehejia, R.H., and S. Wahba. 2002. Propensity Score Matching Methods for Non-Experimental Causal Studies. *The Review of Economics and Statistics* 84(1): 151-161.

Elhorst, J.P. 2005. Unconditional maximum likelihood estimation of linear and log-linear dynamic models for spatial panels. *Geographical Analysis* 37: 85-106.

Elhorst, J.P. 2014a. Spatial Panel Data Models, in Spatial Econometrics (Springer) 37-93.

Elhorst, J.P. 2014b. Spatial econometrics: from cross-sectional data to spatial panels. Springer, Heidelberg.

Elhorst, J.P. 2014c. Matlab software for spatial panels. *International Regional Science Review* 37: 385-401.

Elhorst, J.P. 2017. Spatial Panel Data Analysis. In: Shekhar S., Xiong H., Zhou X. (Eds.) *Encyclopedia of GIS*, 2nd edition, pp. 2050-2058. Springer International Publishing, Cham, Switzerland.

Glasmeier. A., and L. Wood. 2005. Policy Debates Analysis of US Economic Development Administration Expenditure Patterns over 30 Years. *Regional Studies* 39(9): 1261-1274, DOI: 10.1080/00343400500390081.

Haughwout, A. 1999. New estimates of the impact of EDA Public Works Program investments on county labor markets. *Economic Development Quarterly* 13(4): 371-382.

Holtz-Eakin, D., and A.E. Schwartz. 1995. Spatial Productivity Spillovers from Public Infrastructure: Evidence from State Highways. *International Tax and Public Finance* 2:459-468.

Imbens, G. 2004. Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review. *The Review of Economics and Statistics* 86: 4-29.

Kwass, P., B. Siegel, A. Reamer, and B. Roberts. 1992. Evaluation of the U.S. Economic Development Administration's public works program: Analysis and findings (EDA Project No. 99–10–13740). Sommerville. MA: Mt. Auburn.

Lake, R.W., R. Leichenko, and A.K. Glasmeier. 2004. EDA and U.S. Economic Distress: 1965-2000. *EDA Research Report* 99-07-13812.

Larzelere, R.E., and R.B. Cox. 2013. "Making Valid Causal Inferences about Corrective Actions by Parents from Longitudinal Data". *Journal of Family Theory and Review* 5:282–299. doi:10.1111/jftr.12020.

Martin, R., and R. Graham. 1980. The impact of Economic Development Administration programs: some empirical evidence. *Review of Economics and Statistics* 62(1): 52-62.

Moreno, R., and B. Trehan. 1997. "Location and the Growth of Nations", *Journal of Economic Growth* 2: 399-418.

Millo, G., and G. Piras. 2012. splm: Spatial Panel Data Models in R. *Journal of Statistics Software* 47(1): 1-38. URL http://www.jstatsoft.org/v47/i01/.

Munnell, A.H. 1990. Why has productivity growth declined? Productivity and public investment. *New England Economic Review* 1990 (January): 3-22. Federal Reserve Bank of Boston.

Partridge, M.D., and D.S. Rickman. 2008. Place-based policy and rural poverty: insights from the urban spatial mismatch literature. *Cambridge Journal of Regions, Economy and Society* 1: 131–156.

Pender, J., and R. Reeder. 2011. Impacts of Regional Approaches to Rural Development Initial Evidence on the Delta Regional Authority. USDA-ERS Research Report No 119, June 2011.

Pradhan, M., and L. Rawlings. 2002. “The Impact and Targeting of Social Infrastructure Investments: Lessons from the Nicaraguan Social Fund,” *World Bank Economic Review* 16(2): 275-295.

Ravallion, M., and Q.T. Wodon. 1999. Poor Areas or Only Poor People? *Journal of Regional Science* 39(4): 689-711.

Rosenbaum, P.R., and D.B. Rubin. 1983. The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* 70 (1): 41-55.

Rubin, D.B. 1974. Estimating Causal Effects of Treatments in Randomized and Non-randomized Studies. *Journal of Educational Psychology* 66 (5): 688-70.

Rubin, D., 1977. Assignment to a Treatment Group on the Basis of a Covariate. *Journal of Educational Statistics* 2(1): 1-26

Tong, T., T.H.E. Yu., S.H. Cho., K. Jensen, and D.D.L.T. Ugarte. 2013. Evaluating the spatial spillover effects of transportation infrastructure on agricultural output across the United States. *Journal of Transport Geography* 30: 47-55.

Vega, S.H., and J.P. Elhorst. 2015. The SLX model. J. Reg. Sci. http://dx.doi.org/10.1111/jors.12188.

Watts, B., G.A. Erickcek, J. Duritsky, K. O’Brien, C. Robey, and J. Robey. 2011. What should EDA fund? Developing a model for pre-assessment of economic development investments. *Economic Development Quarterly* 25: 65-78.

APPENDICES

Table 3-6 Estimation Results for the OLS models

Independent Variables	Haughwout's (1999) *OLS* (1990 - 1994)	*ln(PNFEMP) OLS* (2010 - 2014)
SMSHARE (%)	-0.007***	-0.008***
Standard error	0.0004	0.0004
BIGSHARE (%)	0.171***	0.258***
Standard error	0.013	0.014
URBAN (1 = MSA county)	0.022***	0.025***
Standard error	0.003	0.003
BLACK (%)	-0.0006	-0.0006***
Standard error	0.0001	0.0001
ln (MHV) (natural log / $)	0.088***	0.048***
Standard error	0.005	0.005
ln (PNFEMP) (natural log)	0.964***	0.962***
Standard error	0.001	0.002
ln (EDA) (natural log / $)	0.0009**	0.0009*
Standard error	0.0003	0.0005
State and year fixed effects?	Yes	Yes
Observations	15,054	15,330
R squared	0.9942	0.9997
Adjusted *R* squared	0.9941	0.9997

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level.

Table 3-7 State and Year Fixed-Effects on U.S. County Employment Levels

Dependent Variable lnPNFEMP	**OLS Fixed Effects Model**	
Alabama	0.223***	(0.057)
Arizona	0.283***	(0.060)
Arkansas	0.268***	(0.056)
California	0.185***	(0.062)
Colorado	0.232***	(0.060)
Connecticut	0.256***	(0.065)
Delaware	0.277***	(0.072)
District of Columbia	0.347***	(0.096)
Florida	0.288***	(0.059)
Georgia	0.236***	(0.057)
Idaho	0.202***	(0.059)
Illinois	0.260***	(0.056)
Indiana	0.240***	(0.056)
Iowa	0.269***	(0.056)
Kansas	0.273***	(0.056)
Kentucky	0.229***	(0.055)
Louisiana	0.304***	(0.057)
Maine	0.299***	(0.060)
Maryland	0.249***	(0.061)
Massachusetts	0.283***	(0.063)
Michigan	0.264***	(0.057)
Minnesota	0.275***	(0.057)
Mississippi	0.256***	(0.057)
Missouri	0.265***	(0.056)
Montana	0.304***	(0.058)
Nebraska	0.320***	(0.056)
Nevada	0.161***	(0.061)
New Hampshire	0.234***	(0.063)
New Jersey	0.259***	(0.062)
New Mexico	0.180***	(0.059)
New York	0.316***	(0.058)
North Carolina	0.227***	(0.057)
North Dakota	0.404***	(0.056)
Ohio	0.236***	(0.056)
Oklahoma	0.296***	(0.056)
Oregon	0.254***	(0.060)
Pennsylvania	0.294***	(0.057)
Rhode Island	0.236***	(0.068)
South Carolina	0.255***	(0.058)
South Dakota	0.323***	(0.056)
Tennessee	0.214***	(0.056)
Texas	0.295***	(0.056)
Utah	0.200***	(0.060)
Vermont	0.256***	(0.062)
Virginia	0.206***	(0.058)
Washington	0.222***	(0.06)
West Virginia	0.232***	(0.056)
Wisconsin	0.247***	(0.057)
Wyoming	0.269***	(0.060)
2011	0.003	(0.004)
2012	0.020***	(0.004)
2013	0.022***	(0.004)
2014	0.033***	(0.004)

Notes: Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5%, and 1% level.

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